Evaluating Predator Prey Dynamics and Site Utilization Patterns of Golden Eagles using Resource Selection Modeling and Spatiotemporal Pattern Mining

by

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A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

August 2019

To my girlfriend Alex McBride and parents George and Robin Galloway. Thank you for the late-night reassuring conversations and unrelenting support. Without you this would not have been possible.

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Acknowledgements

I am grateful to my mentor, Professor Kemp, for always making herself available and providing me the direction I needed to complete this study. Additionally, I would like to express my gratitude to my committee members, Dr. Laura Loyola, Dr. An-min Wu, and Dr. Travis Longcore for providing invaluable advice throughout this process. A special thank Dr. Doug Bell, Dr. Shawn Smallwood, and Lee Neher for the guidance and expertise that made this entire study possible. I would like to thank East Bay Regional Park District and Dr. Doug Bell for allowing me to analyze the golden eagle telemetry data. Additionally, I am grateful to Dr. Shawn Smallwood allowing me to analyze the California ground squirrel burrow location data that he has been collecting for the past 20 years. Without these data, this study would not have been possible. I would also like to thank Lee Neher for the work he put into aggregating the telemetry data used in this analysis. Finally, I would like to thank my supervisors, Robert Carey and Laura Finley, who allowed me to have a flexible schedule when needed to complete my thesis on time.

List of Abbreviations

ASCII	American Standard Code for Information Interchange
AWEA	American Wind Energy Association
AIC	Akaike Information Criteria
AUC	Area under the curve
CI	Confidence interval
DEM	Digital elevation model
EHSA	Emerging Hot Spot Analysis
EVT	Existing vegetation type
GIS	Geographic information system
GLM	Generalized linear model
GLMM	Generalized linear mixed models
GPS	Global positioning system
LOOCV	Leave-one-out cross-validation
NDVI	Normalized difference in vegetation index
NIR	Near infrared
NRCS	Natural Resource Conservation Service
ROC	Receiver operating characteristic
RSF	Resource selection function
SDM	Species distribution model
SPI	Slope position index
STC	Space Time Cube
TPI	Topographic position index

UD	Utilization distribution
USGS	United States Geological Survey
VRM	Vector ruggedness measure

Abstract

Within the United States, wind energy has a steady growth rate, with an estimated installed capacity of 95-million mega-watts as of 2018. Despite the benefits associated with wind energy, there are negative impacts from wind energy facilities to avian species, ranging from collisions with site infrastructure and electrocution to habitat conversion. Golden eagles (*Aquila chrysaetos*) are one of the most studied species, in regards to wind energy expansion, due to their federally protected status and sensitivity to decreases in population numbers from anthropogenic sources. Studies have evaluated how golden eagles use their environments in order to better understand the conditions that result in increased fatality rates. This study evaluated the effect of prey distribution on non-adult golden eagles' resource selection and used spatiotemporal pattern mining tools to evaluate patterns of habitat use at the Altamont Pass Wind Resource Area (Altamont).

To evaluate the relationship between California ground squirrels (*Otospermophilus beecheyi*) and golden eagles, a species distribution model (SDM) was developed in Maxent for ground squirrels using burrow distribution as a proxy to estimate the ground squirrel distribution at the Altamont. The SDM output had good predictive capacity and was used in a resource selection function (RSF) model in R to evaluate if ground squirrel distribution affected resource selection of non-adult golden eagles. The resulting RSF model performed poorly, thus the influence of ground squirrel distribution on non-adult golden eagle resource selection remains largely unknown. Telemetry data was then analyzed using spatiotemporal hot spot analyses to identify patterns of use over space and time in ArcGIS Pro. Despite the inconclusive RSF model results, space-time pattern mining identified the hot spots of eagle activity within the Altamont, which could be a starting point for future analyses.

Chapter 1 Introduction

There is a global push for the development and implementation of renewable energy sources to offset the effects of climate change resulting from increased carbon emissions. Renewable energy is typically defined as sources of energy continuously occurring from natural processes or phenomena (e.g. sun, wind, or water) (Ellabban, Abu-Rub and Blaabjerg 2014). To harvest renewable energy, production plants such as solar arrays or wind facilities are installed where the resource occurs. These sources of energy are anticipated to help reduce the carbon footprint of fossil-based fuel types minimizing the contribution to global warming (Table 1).

Table 1 - Negative effects of various types of energy production. Data from Singh et al. (2016).

Environmental Impacts	Coal	Natural Gas	Oil	Nuclear	Hydropower	Wind
Air or Water Pollution	X	X	X			
Global Warming	X	X	X			
Thermal Pollution of Water				X		
Flooding of Land					X	
Waste Disposal	X			X		
Mining and Drilling	X	X	X	X		
Construction of Processing Plants	X	X	X	X	X	X

1.1. Effects of Wind Energy Production on Wildlife

Wind energy production within the United States is steadily increasing, with a production capacity exceeding 95 million megawatts in 2018 (Figure 1) (American Wind Energy Association 2018, Allison et al. 2017, Pinger 2013). While wind energy production helps to offset the negative effects of traditional energy sources on climate change, there are still negative impacts on wildlife (Smallwood 2007). The most common species affected by wind energy production are avian and chiropteran species through collision with turbines (e.g. mast or blades), reduction in habitat, or electrocution from site infrastructure (e.g. transmission poles) (Smallwood 2007).

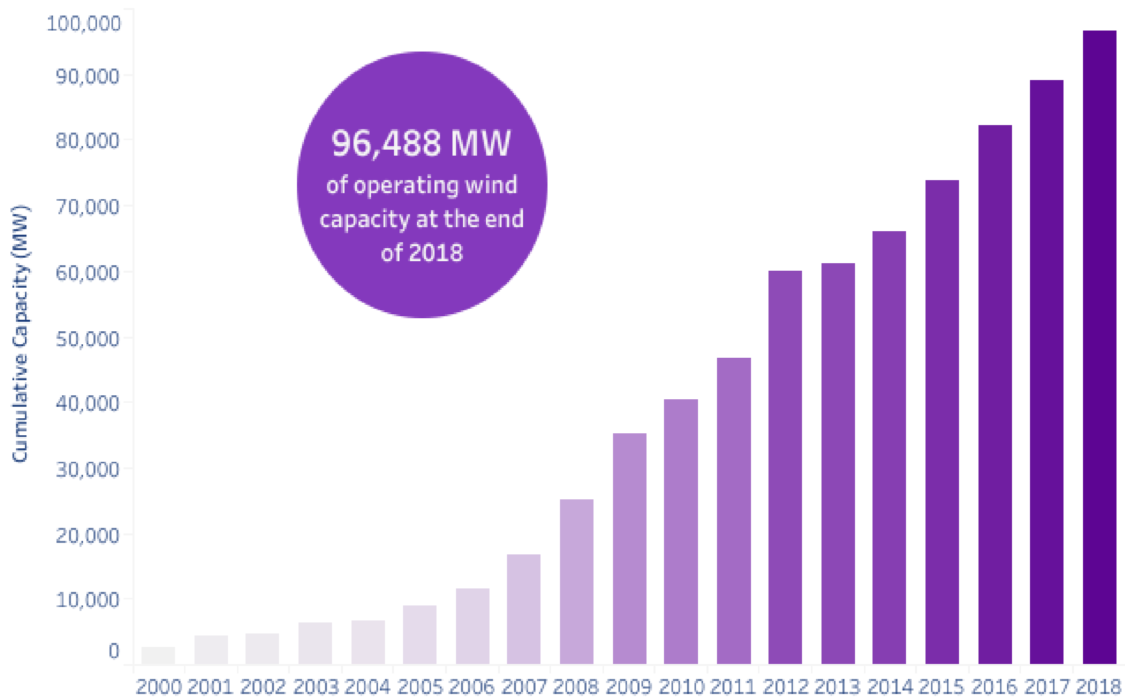


Figure 1 – The United States wind energy production capacity as of 2018. Source: American Wind Eenergy Association 2018.

While avian fatality rates at wind facilities are less than those caused by other anthropogenic sources (e.g. buildings or highways), these effects can have long-lasting negative impacts on avian populations (Sovacool 2009, Sovacool 2013, Erickson, Johnson, and David 2005, Erickson et al. 2001, Marques et al. 2014, May et al. 2017, Watson et al. 2018). These effects on wildlife are a cause for concern as new wind energy developments are planned. Research is ongoing to develop methods to quantify fatalities, improve site design, and understand how species use their environments (Watson et al. 2018, May et al. 2017). The ability to understand factors that contribute to avian fatalities allows land managers to develop and implement mitigation strategies to offset these impacts.

Metanalyses reviewing wind energy and wildlife conflict have compiled results from several studies that evaluated how wind facility and species characteristics influenced avian fatalities (Marques et al. 2014, Kikuchi 2008, Watson et al. 2018). These reviews cite characteristics such as the environmental conditions (e.g. weather, topography), site configuration, behavioral and morphological traits of affected species, prey distribution and density, as well as several other factors. However, it is likely that the exact causes of avian fatalities at wind farms are highly site-, species-, or individual-specific, which makes it challenging to apply effective mitigation strategies from one facility to the next (Watson et al. 2018, Marques et al. 2014). However, understanding how various resources are used by different species can provide land managers with more options to determine what mitigation strategies work best for their site.

1.2. Research Objectives

The scope of this study was to determine the distribution of California ground squirrel (ground squirrels; *Otospermophilus beecheyi*) burrows at the Altamont Pass Wind Resource Area (the Altamont or study area) and to evaluate if their distribution influences the resource selection of non-adult golden eagles (*Aquila chrysaetos*). Additionally, this analysis used spatiotemporal pattern mining to identify trends in non-adult golden eagle site use. The intent of this study was to provide answers to the following questions:

1. What is the distribution of potential ground squirrel habitat at the Altamont based on historic burrow locations?
2. Do non-adult golden eagles select locations while flying that have higher relative probabilities of ground squirrel occurrence?

3. Have trends in space use varied over the study period (2012 – 2018), or are there consistent patterns of use among non-adult golden eagles?

The results of this study will provide land managers with additional resources to assess patterns of use by both ground squirrels and non-adult golden eagles for improved resource management.

1.3. Overview of Study Design

To accomplish the research goals in Section 1.2, this analysis was conducted in three phases. Phase one developed a species distribution model (SDM) for the ground squirrels within the Altamont based on burrow locations. The spatial model output (layer) provided the relative probability of occurrence of ground squirrel within the Altamont. This layer was then utilized as a variable for non-adult golden eagle resource selection modeling in Phase two.

The second phase of this analysis developed resource selection function models (RSF), a statistical tool for analyzing how animals use their habitat, for non-adult golden eagles within the Altamont. The RSF incorporated both common environmental variables and the result of the ground squirrel model from phase one to understand resource selection. The results can help identify important resources for non-adult golden eagles, determine if ground squirrel distribution influences resource selection, and show where the highest relative probabilities of selection occur within the Altamont.

Finally, Phase three used hot spot analyses, space-time cube (STC) hot spot analysis, and emerging hot spot analyses (EHSA) to explore the spatial and temporal trends of use at the Altamont by non-adult golden eagles. The results can be used to evaluate how resource selection corresponds with changing patterns of use at the Altamont. Using these methods, the resulting output maps can identify areas of increased use by individuals and provide managers with another lens through which to assess the potential risk to non-adult golden eagles.

The aforementioned phases are detailed in the following chapters. Chapter 2 provides background on wind and wildlife interactions at wind facilities, the study area, and common approaches to SDM and RSF modeling. Chapter 3 describes the ground squirrel distribution modeling process. It begins with a brief introduction to the life history and management background of ground squirrels at the Altamont and then details the SDM variable selection and exploration, model settings, and validation of the SDM for ground squirrels. It ends with a discussion of the results of the ground squirrel modeling effort. Chapter 4 describes the golden eagle resource selection modeling process. It begins with an overview of the golden eagle life history, then discusses home range identification, variable selection for the RSF model, the structure of the non-adult golden eagle RSF, and model validation. It concludes with a discussion of the results and the predictive strength of the model. Chapter 5 uses hot spot analyses, space-time cube (STC) hot spot analysis, and emerging hot spot analyses (EHSA) to analyze patterns of use by non-adult golden eagles at the Altamont over the course of the study period. Finally, Chapter 6 considers the results of this analysis in the aggregate, discusses the implications of this modeling approach, and provides recommendations for future analyses.

Chapter 2 Background

Over the past 30-years, scientists have been researching the factors associated with increased collision rates of avian species with wind energy site infrastructure and the potential impacts on avian populations (Watson et al. 2018). While population-level impacts may be less distinguishable immediately, behavioral analyses can provide great insight into how animals use their environments. Information derived from these studies is vital to land managers who recommend and implement mitigation strategies before a population level response occurs (May et al. 2017).

The following chapter provides background on wind and wildlife interactions, study area ecology and history, methods for analyzing species distribution and resource selection, and finally, ways to visualize spatial and temporal trends of animal territory use. This information is intended to provide the reader with the necessary background knowledge to understand the methods used to explore species distribution, resource selection, and spatiotemporal patterning analysis used within this analysis.

2.1. Wind Energy Production Impacts to Avian Species

Wind energy production has both direct (e.g. collisions) and indirect impacts (e.g. ecosystem alteration) on avian species (Figure 2). The magnitude of these impacts is highly variable depending on site location, facility design, species morphology, and frequency of use (e.g. migration corridor) (Kuvlesky et al. 2007, Sinclair et al. 2018). Raptor species typically have lower reproductive output, are slower to reach sexual maturity, and are long-lived. These avian species are at greater risk for both collision and long-lasting population effects, compared to smaller passerine species due to differences in life history strategies (Hunt 2002, Hunt and Watson 2016, Watson et al. 2018). As a result, raptor species are less able to absorb the effects of mortality from anthropogenic sources and are more likely to experience local population declines.

Figure 2 - Raptor carcass on wind turbine pad. Photo credit: Hedy Ben Eliahou, in Rinat (2017).

Habitat requirements for many raptor species often coincide with preferred environmental and landscape characteristics for wind energy production (e.g. steep topography, high degree of terrain variability, high average wind speeds) predisposing these individuals to high collision potential with site infrastructure (Pagel et al. 2013, Mojica, Watts, and Turrin 2016, Miller et al. 2014). For example, the large wingspan of raptors reduces maneuverability and increases energetic demands requiring updraft to aid flight, which also corresponds with favorable wind production locations. There are several theories surrounding why certain species are more susceptible to collision such as resource overlap, inter- or intraspecies dynamics, and prey distribution (Marques et al. 2014, Watson et al. 2018).

2.1.1. Turbine Design and Placement

Because of the degree of overlap between raptor resource selection and wind energy production, it is hypothesized that turbine location, design, and density influence collision potential (Figure 3) (Smallwood and Neher 2009, Pinger 2013). However, wind turbine design, placement, array characteristics, and subsequent impacts to avian species, likely vary by site

(Marques et al. 2014, Watson et al. 2018). Therefore, while there is no "one size fits all" approach to understanding which turbine characteristics pose the highest risk to avian species, it is useful to understand the range of these potential influences to better inform mitigation strategies.

Figure 3 - Turbine array with tubular style turbines. Photo credit: Andrew Burmester.

Common site and turbine features attributed to higher collision risk included turbine density, site configuration, and turbine mast or blade visibility (Marques et al. 2014, Pinger 2013, Watson et al. 2018, Smallwood 2007). At the Altamont, raptor fatalities were found to be positively correlated with turbines at the end of rows and edges of turbine clusters (Pinger 2013, Smallwood and Thelander 2005). Topographic position of turbines has been found to increase collision risk, where turbines located on lower/mid slopes and saddles were positively correlated with avian fatalities (Pinger 2013). Turbine height, style, and rotor size have also been documented to influence avian fatality rates, but these parameters are likely associated with other important environmental characteristics (de Lucas et al. 2008).

2.1.2. Avian Abundance

Other than turbine related attributes, species abundance and interactions with conspecifics have been thought to increase collision risk, as they may result in different behavior

(Marques et al. 2014, de Lucas et al. 2008, Watson et al. 2018). While these interactions may increase the risk of collision, abundance studies have not found a relationship between species abundance and collision risk; but this may vary by site. In contrast, there are hypotheses that migrating birds, especially large flocks, may be highly susceptible due to lack of familiarity with the site, poor weather conditions, or migration flight heights (Miller et al. 2014, Marques et al. 2014). Behavioral studies at the Altamont have documented raptors interacting with conspecifics near turbines, which is thought to increase collision risk due to reduced turbine perception (Smallwood and Karas 2009). However, behavioral interactions are difficult to quantify and vary by site and are more likely a function of territory distribution and species/intraspecies dynamics.

2.1.3. Effect of Prey Distribution and Foraging

The prevalence of prey resources at wind farms also has been cited as a potential driver for increased use and collision risk (Watson et al. 2018, Smallwood et al. 2009, Smallwood, Morrison, and Rugge 2009, Marques et al. 2014). Similar to conspecific interaction, it has been thought individuals that are foraging near turbines may become fixated on a prey resource increasing collision risk. Additionally, age has been thought to influence foraging competences and subsequent collision risk (Watson et al. 2018). Researchers have suggested that adults are more susceptible to collisions when hunting because they are more adept at identifying prey resources, and non-adults are less likely to key in on these features resulting in the greater perception of obstacles. Moreover, many of the flight behaviors associated with foraging, such as lower flight heights, concealment behind ridges, contouring, stooping, and kiting, often coincide with rotor swipe zones of turbines (Smallwood, Rugge, and Morrison 2009, Hunt 2002, Smallwood et al. 2009). The effect of prey, like many of the other factors, is likely individual- and site-specific.

2.2. The Altamont Pass Wind Resource Area

Since the start of operations in the 1970's, there have been several thousand reported avian fatalities at the Altamont Pass Wind Resource Area representing approximately 70 species; of which many are protected by state or federal law (Smallwood 2007). As a result of this and legal challenges, a Scientific Review Committee was formed with membership appointed by the wind energy stakeholders, environmental community, County Planning Department, California Energy Commission or Department of Fish and Wildlife, and U.S. Fish and Wildlife Service to review and provide guidance on implementation of scientific research related to the wind resource area. The members of the SRC are Dr. Joanna Burger, Jim Estep, Sue Orloff, Dr. Julie Yee, and Dr. Mike Morrison. Given the documented high avian fatality rates throughout the 1990's, the Altamont became one of the most consistently studied wind farms in the world for wind energy and wildlife conflict (Smallwood and Thelander 2008, Erickson et al. 2001, Pinger 2013). These localized studies attempt to identify the wind farm's impact on avian species and develop mitigation strategies to reduce these impacts. Since the initiation of the Scientific Review Committee, numerous studies have evaluated the environmental impact of the Altamont and have recommended several mitigation strategies such as painting turbine blades to increase visibility, changing site design, and using limited operating periods.

2.2.1. Site Description

The Altamont is located in the Diablo Mountain Range in central California, straddling Alameda and Contra Costa counties (Figure 4) (Smallwood and Thelander 2008). Since the 1980s, the 175km^2 wind resource area has included anywhere from 4,000 to 5,000+ turbines with several different turbine models, production companies, and tower types (lattice, tubular, and vertical access) (Smallwood and Thelander 2008, Pinger 2013, Leslie 2015, Smallwood 2007).

The number of turbines in operation within the Altamont varies based on the development stage (e.g. site expansion) and repowering initiatives.

Figure 4 - The Altamont Pass Wind Resource Area and study area boundary

The terrain at the Altamont consists of rolling hills and ridges, with elevations ranging from approximately 30 to 650 meters above sea level. The primary vegetation type at the Altamont consists of California annual grasslands and non-native grass species transitioning to an oak woodland ecosystem to the north of the study area (Smallwood and Thelander 2008). The Altamont, shown in Figure 5, is bordered by development to the east and west with the cities of Tracy and Livermore and there is a large reservoir located in the north (Kolar and Wiens 2017). Within the Altamont, land use includes cattle grazing, wind energy production, mining, waste management, and agriculture (Smallwood and Karas 2009).

Figure 5 - The Altamont Pass Wind Resource Area. Photo credit: Michael Macor, The Chronicle.

Wind patterns in the Altamont originate from varying directions typically associated with "sea breeze" circulation (Smith 1987, Smallwood and Thelander 2008). Prevailing winds come from the southwest and northwest directions. However, with some seasonal weather patterns, winds can from east and northeast directions. During the months April to September, this area is subject to 25 to 45kph winds making it ideal for energy production (Leslie 2015, Smith 1987).

2.2.2. Effects to Golden Eagles

The Diablo Mountain Range is home to several territorial pairs of golden eagles (Wiens et al. 2018, Hunt 2002, Hunt et al. 2017, Kolar and Wiens 2017). Surveys near the Altamont indicate that there are at least 58 to 61 territorial pairs within 30km of the Altamont and at least 88 to 89 territorial pairs within the greater Diablo Mountain Range. The Altamont has extremely high fatality rates for golden eagles, especially within the sub-adult age classes, with fatality estimates ranging from 55 to 65 individuals per year (Smallwood and Karas 2008, Wiens et al. 2018, Hunt 2002). These estimates imply that there have likely been anywhere from 1,000 to 2,000 individuals killed by turbines since the start of operations (Watson et al. 2018).

2.2.3. History of Mitigation Strategies

The golden eagle is federally protected under the Bald and Golden Eagle Protection Act and the Migratory Bird Treaty Act (USFWS 2013). Take of this species is prohibited and enforced by the United States Fish and Wildlife Service. While mechanisms exist to mitigate turbine caused mortality, there are limited federal regulations requiring companies to implement these strategies (Singh, Baker, and Lackner 2015, Drewitt and Langston 2006, Smallwood 2007). To offset the effect of the take at the Altamont, several mitigation strategies have been recommended to the Scientific Review Committee by researchers (Smallwood 2007). These recommendations have included painting turbine blades to increase visibility, installing use deterrents (e.g. audible deterrents), reducing grazing around turbines to reduce the visibility of ground squirrels, moving rock piles from turbines to prevent use by ground squirrels, and the decommissioning and removal of old or non-operating turbines. However, there have been varying degrees of implementation of these strategies.

2.3. Methods for Assessing Species Distribution and Resource Selection

Resource selection by animals is the process by which resources that are essential to breeding, feeding, or sheltering are either selected for or utilized by an individual (Northrup et al. 2013, Millspaugh et al. 2006). By understanding resource selection, insight on species behavior, distribution, and resource preferences allow land managers to better understand the potential impacts of management decisions. To understand the relationship between animals and their environments, statistical methods, such as regression or maximum entropy techniques, are used to model species distribution and resource selection. These techniques use a combination of presence and absence points, or presence and available points, to generate a relationship between presence points and absence/available locations that estimate the relative probability of occurrence or selection across the entire study area (Lele et al. 2013). Two commonly used methods for understanding geographic distribution and habitat use, are species distribution modeling (SDM) and resource selection function (RSF) modeling.

2.3.1. Species Distribution Modeling

Species distribution, or environmental niche, modeling is a form of statistical modeling that uses presence locations, absence or background locations, and environmental variables to identify the spatial distribution for a species of interest (Figure 6) (Elith et al. 2011, Merow, Smith, and Silander 2013). Species distribution models can be created using classical regression techniques (e.g. generalized linear model), random forests, or maximum entropy approaches (Manly et al. 2002). Inconsistencies in data collection, small sample sizes, and presence only datasets make using traditional presence-absence modeling techniques inappropriate (Merow, Smith, and Silander 2013). When compared to traditional statistical methods, maximum entropy models have shown equitable results while having more relaxed assumptions. This is appealing for datasets not able to meet the assumptions of traditional statistical methods (Elith et al. 2011).

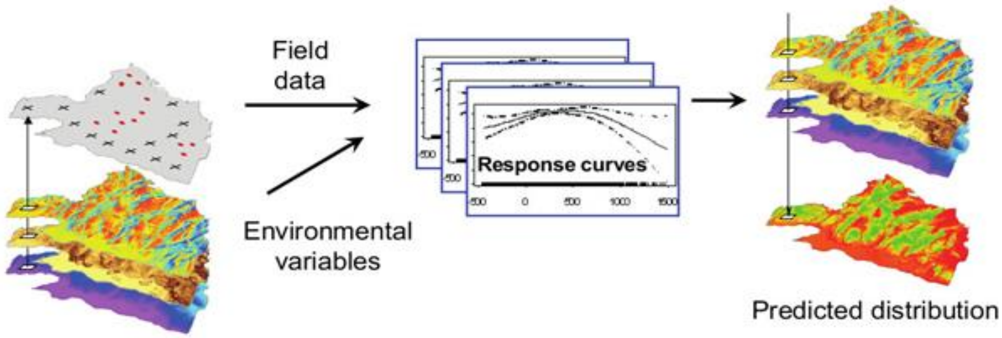


Figure 6 - Species distribution model general workflow. Source: Antione Guisan, in Hordijk (2016).

Maximum entropy models fit a geographical distribution of a species by finding the tightest fit between presence and background locations under the set of constraints applied through environmental covariates (Phillips et al. 2017). While there are several maximum entropy software packages used in the literature (e.g. Maxent, MaxNet, and Maxlike in R), there is no consensus on which maximum entropy method is most appropriate.

Thousands of analyses used Maxent to develop SDMs and the approach has been widely published in modeling literature (Merow and Silander 2014, Phillips et al. 2017). However, due to the "black box" nature of the program and history of misuse, the Maxent approach has been subject to much debate. Like any modeling approach, great care needs to be taken when selecting predictor variables, evaluating underlying assumptions, testing model performance and fit, and validating results (Merow, Smith, and Silander 2013, Merow and Silander 2014). If these steps are done appropriately, then Maxent can be an incredibly useful tool.

Within the Maxent program, the user can specify several statistical relationships, called feature classes, that can be used to fit different relationships with the data (Merow, Smith, and Silander 2013, Phillips, Anderson, and Schapire 2006). The feature classes include linear, quadratic, product, hinge, and threshold. The program defaults to include the linear, quadratic, product, and hinge features; however, users are encouraged to think about their data and apply feature classes that make sense (Baldwin 2009, Merow, Smith, and Silander 2013). For example, if threshold features are used, then the model may establish a cutoff point essentially turning the variable into a binary factor. However, if there is not a biologically justifiable reason to do this, the user may not want to include this feature class. Feature classes are used during the modeling process based on the number of presence points included. More complex relationships will be used in model fitting with greater numbers of presence points (Phillips, Anderson, and Schapire 2006).

Maxent also provides the ability for users to tune models which can reduce the risk of selecting an overfit model by using the regularization multiplier (Merow, Smith, and Silander 2013). The Maxent algorithm penalizes more complex models; similar to information criterion approaches, and relaxes the model constraints to not fit the model too precisely. Higher regularization multiplier values penalize overly complex models which allow the user to evaluate model behavior. Model tuning is an iterative process that requires users to fit several identical models using different regularization multiplier values. By observing differences in model behavior, the user is able to make an informed selection between more complex potentially overfit models and less complex models.

Maxent model predictions can be displayed spatially using various model output formats which include the cloglog, logistic, raw, and cumulative forms (Phillips, Anderson, and Schapire 2006, Phillips et al. 2017). Some studies have suggested that the raw form is preferred, where each cell is given a probability value and all cells add to be one (Merow, Smith, and Silander 2013). However, the raw output can be problematic if the area being modeled has hundreds of thousands of cells because output values are so small, it is therefore hard to interpret the meaning of the model results. The creators of the program recommend using cloglog or logistic formats because the probability of occurrence is scaled from 0 to 1 (Phillips, Anderson, and Schapire 2006, Phillips et al. 2017). However, this approach comes with the caveat of assuming an unknown detection probability. Because the detection probability is unknown, the result is not a true probability but relative probability, which may be fine depending on the goals of the study (Merow, Smith, and Silander 2013). The final relative prediction output can be exported as a raster file and further analyzed using a GIS.

2.3.2. Resource Selection Function Modeling

Resource selection function modeling has been used as a means to better understand how habitat selection correlates to resource distribution across a landscape (Aarts et al. 2013, Millspaugh et al. 2006). These models statistically evaluate the relative difference in resource selection/avoidance in proportion to its availability. Developing the relationship between selected and available resources can show how the individual or study animal's preference for resources influences the relative probability of selection.

Resource selection functions can be developed using a variety of statistical techniques including GLMs, generalized linear mixed effects models (GLMM), regression trees, generalized estimating equations, and several other types of linear and additive techniques (Zuur et al. 2009). Resource selection functions can be created for various scales for which the individual would select resources (e.g. where to establish a territory or where to forage within a territory), referred to as orders, which have different practical applications for ecologists (Johnson 1980). Choosing between methods and orders is highly dependent upon the data available and the inferences drawn from these data (Zuur et al. 2009).

There is specific terminology used for RSFs that is important to understand (Lele et al. 2013). In RSFs, a resource is defined as an item that is distributed across a landscape which is available for selection by an individual within the study. For this study, the term fixed effects refers to each variable (e.g. vegetation type) that occur at each level (Bolker et al. 2009). Random effects are broken into two categories, random effects and individual level random effects. Random effects are those effects that evaluate within-group variation (e.g. random intercept) and individual level random effects are those that evaluate within individual variation (e.g. random slopes). The use of various random effects allows ecologists to model habitat preferences across different sampling periods and individuals with varying amounts of subsamples.

Resource selection by individuals takes place at multiple scales and each scale represents potential differences in niche requirements (Johnson 1980). The multiple scales of selection have been broadly categorized into orders of resource selection. Johnson notes that, although there are many variations, the orders of resource selection have been generally grouped into four categories. First order resource selection occurs at the range or geographical distribution of the species. Second order resource selection determines the home range within the geographical range of the species. Third order resource selection is specifically looking into resources selected within an individual’s home range. Finally, fourth order selection refers to the actual acquisition of resources from specific habitat patches.

It is worth noting that new methods have been developed to model third order resource selection called resource utilization functions, where the intensity of use is estimated from kernel-based utilization distribution (UD) estimates (Marzulff et al. 2004, Long et al. 2009). However, these are only appropriate if the true magnitude of use can be accurately estimated (e.g. being able to delineate an entire home range), otherwise, this method can result in biased inferences (Long et al. 2009).

2.3.2.1. Generalized Linear Mixed Models

When analyzing wildlife telemetry data several problems can occur such as transmitter failure, spatial and temporal autocorrelation, and differences in sample sizes/duration which may make GLMs inappropriate for analysis (Koper and Manseau 2010). When these abnormalities occur, mixed effects model approaches are used to allow for an estimation of resource selection which is robust to these types of errors (Bolker et al 2009). Generalized linear mixed models (GLMM) are increasingly used in the field of ecology to cope with various problems introduced from using GPS telemetry data and provide reliable estimates for animal resource selection.

One of the more commonly used GLMM packages in R is *lme4* with its *glmer* function (Bates et al. 2015). The two types of resource selection models that can be developed, depending on the data available, are a presence-absence design allowing for the development of a resource selection probability function and a used-available design which results in an RSF (Lele et al. 2013). Within this study, the data available are a used-available format which estimates the relative probability of selection using Equation 1.

$$w(x) = \exp(\beta 1x1 + \beta 2x2 + \cdots + \beta txt) \tag{1}$$

Where w(x) is the log-odds relative probability of selection, β represent the independent variable, and x represents the parameter estimate (Long 2018). The presence-absence study design is preferred because it allows for the true probability of selection to be inferred. However, the used-available study design, which estimates the relative probability of selection, can still yield a great deal of information about how individuals perceive their environment (Zuur et al. 2009).

Assumptions associated with developing RSFs include: the sample is representative of the population; units are independent; selection of resources is independent of other units (e.g. members of a herd); resource availability is known and remains constant over the study period, and selection of resources are measured correctly (Long 2018). In addition to these assumptions, the assumptions of the GLMM are comparable to other regression techniques including independence of samples and no evidence of heteroscedasticity, overdispersion, or zero inflation (Zuur et al. 2009, Zuur, Ieno, and Elphick 2010, Bolker et al. 2009). To ensure the resulting model is reliable, it is critical to determine that the data used are appropriate for the modeling method and that the model results are consistent with the underlying assumptions.

2.3.3. Resource Selection Models for Golden Eagles

Numerous modeling approaches have been used to study resource selection by golden eagles. Commonly used techniques to estimate resource selection include linear regression models such as GLMMs and generalized estimating equations (Watson, Duff, and Davies 2014, Tikkanen et al. 2018, Miller et al. 2014, LeBeau et al. 2015). Several telemetry-based studies have used these approaches to evaluate preferences in resource and habitat use by golden eagles. The results from these provide important insight into specific environmental and abiotic factors that frequently influence selection by golden eagles.

Across golden eagle RSF studies, the set of biotic and abiotic variables included was relatively consistent and choice of variables used in each was primarily influenced by the study objectives (Watson, Duff, and Davies 2014, LeBeau et al. 2015, Nielson et al. 2016, Tikkanen et al. 2018, Miller et al. 2014, Domenech et al. 2015). Variables used in all models measured terrain heterogeneity, vegetation, land use type, wind, population metrics, and prey species habitat. Where variables measuring wind, vegetation, prey species habitat, and topographic heterogeneity were identified as important predictors in golden eagle resource selection.

The variable “distance to nest” was used in several models for determining territory use or population influences, and positively influenced selection (LeBeau et al. 2015, Tikkanen et al. 2018, Watson, Duff, and Davies 2014, Nielson et al. 2016). Other positively associated variables included “distance to prey habitat”, “proportion of an area comprised of prey habitat”, and degree of terrain heterogeneity (LeBeau et al. 2015, Wiens et al. 2018, Miller et al. 2014). Land use types such as grasslands positively influenced selection and development resulted in avoidance. Methods used to evaluate wind frequently used lift potential metrics such as brightness/solar radiation or orographic lift, which were associated with selection (LeBeau et al. 2015, Miller et al. 2014, Neilson et al. 2016). Generally, the variables nest location, terrain ruggedness, vegetation, land use type, and orographic lift were the most common for predicting resource selection by golden eagles.

2.4. Visualizing Spatiotemporal Patterns in Wildlife Movement

Statistical modeling can provide great insight into how animals perceive and use the surrounding landscape, however, in geospatial sciences, there have been several advances in pattern mining toolsets that enable additional exploration of telemetry-based datasets (Baas 2013). These advances allow data to be aggregated by both spatial and temporal dimensions in order to identify and explore trends that may exist in patterns of use over time. Currently, space-time cubes (STC) and emerging hot spot analyses are most frequently used in the fields of criminology and epidemiology to evaluate patterns in crime or disease outbreaks. However, as Baas points out, they have practical applications for exploring trends in wildlife GPS telemetry data.

2.4.1. Space-Time Cubes

Space-time cubes provide a way to aggregate and visualize spatial data by both geographic and temporal dimensions, where each slice represents a unique spatial and temporal window/bin (Figure 7). Esri has recently popularized this datacube concept, but multidimensional data have been a focus in the remote sensing, oceans and atmospheric communities for some time. Recent advances in GIS software has made STCs easier to develop. The ease in implementation allows a variety of users to evaluate use patterns within point or station data.

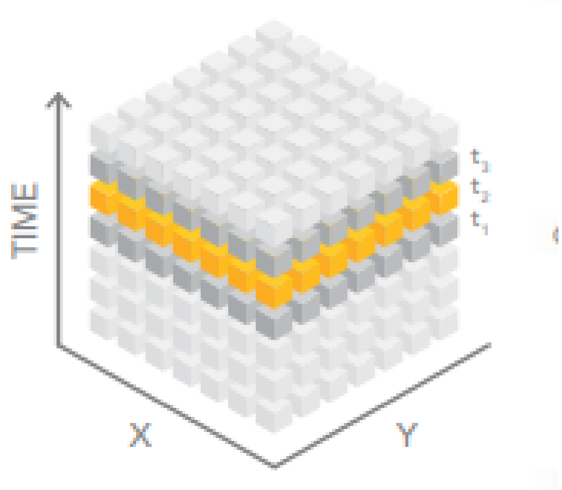


Figure 7 - Structure of a space time cube. Source: Buckley (2018).

In the field of wildlife ecology, these tools have been used for visual exploration of movement patterns, or aggregation of point data from study animals to explore complex spatiotemporal patterns (Kristensson et al. 2009). According to Baas (2013), the use of STCs in wildlife ecology has been minimal and mostly related to the field of movement ecology for species that occupy 3D environments (e.g. birds or aquatic organisms). However, other ecological studies have used space-time pattern mining to monitor trends in deforestation and collision rates between vessels and animals (Bass 2017, Harris et al. 2017). The continued use of these tools has the potential to expand the applications of wildlife telemetry data and will allow scientists to maximize the utility of the data collected.

2.5. Summary

This chapter provided a brief background into conflicts between wind energy resource production and wildlife and discussed ways to evaluate how animals perceive and use their environments. The use of species distribution and resource selection modeling in behavioral ecology has been widely documented and these tools have been shown to be very effective for ecologists and wildlife managers to better understand the systems they manage. Additionally, this chapter introduced less frequently utilized tools such as the innovative STC for visualizing space-time data and exploring complex trends in geographic space.

Chapter 3 California Ground Squirrel Species Distribution Modeling

California ground squirrels (ground squirrels) are habitat generalists capable of occupying a range of environments, providing there are sufficient levels of resources to facilitate breeding, feeding, and sheltering (Hubbart 2012). In order to model ground squirrel distribution, it is critical to understand the primary needs of the species. This chapter details the ground squirrel species distribution modeling component of this project. The goal of this component is to determine the potential distribution of ground squirrels at the Altamont. If successful, the results can be used as a proxy for prey availability in the golden eagle resource selection function model described in the next chapter.

The sections in this chapter include the general life history and resource requirements for ground squirrels; an overview of ground squirrels within the Altamont; discussion of how the variables used for modeling in this project meet ground squirrel resource requirements; a review of the model settings; and discussion of the model results.

3.1. Background: Ground Squirrels

Ground squirrels (*Spermophilus beecheyi*) are semi-fossorial mammals distributed throughout most of California, Baja Mexico, portions of western Oregon and Nevada, and southern Washington shown in Figure 8 (Hubbart 2012, Timm, Álvarez-Castañeda, and Lacher 2016). Ground squirrels play a significant role in ecological food webs for many predatory species (e.g. foxes, snakes, raptors), assist in seed distribution for plants via forgotten food cashes, and provide habitat resources for ground-nesting birds and amphibians (Smallwood and Thelander 2004, Hubbart 2012, Rabin, Coss, and Owings 2006). While ecologically important, ground squirrels are also considered a pest, or nuisance, species because of rangeland forage competition, crop damage, and being vectors for insects and diseases (e.g. fleas, ticks, plague)

(Hubbart 2012). Being a habitat generalist, ground squirrels occupy annual grasslands, oak savannahs, meadows, agricultural lands, and other forested and urban environments.

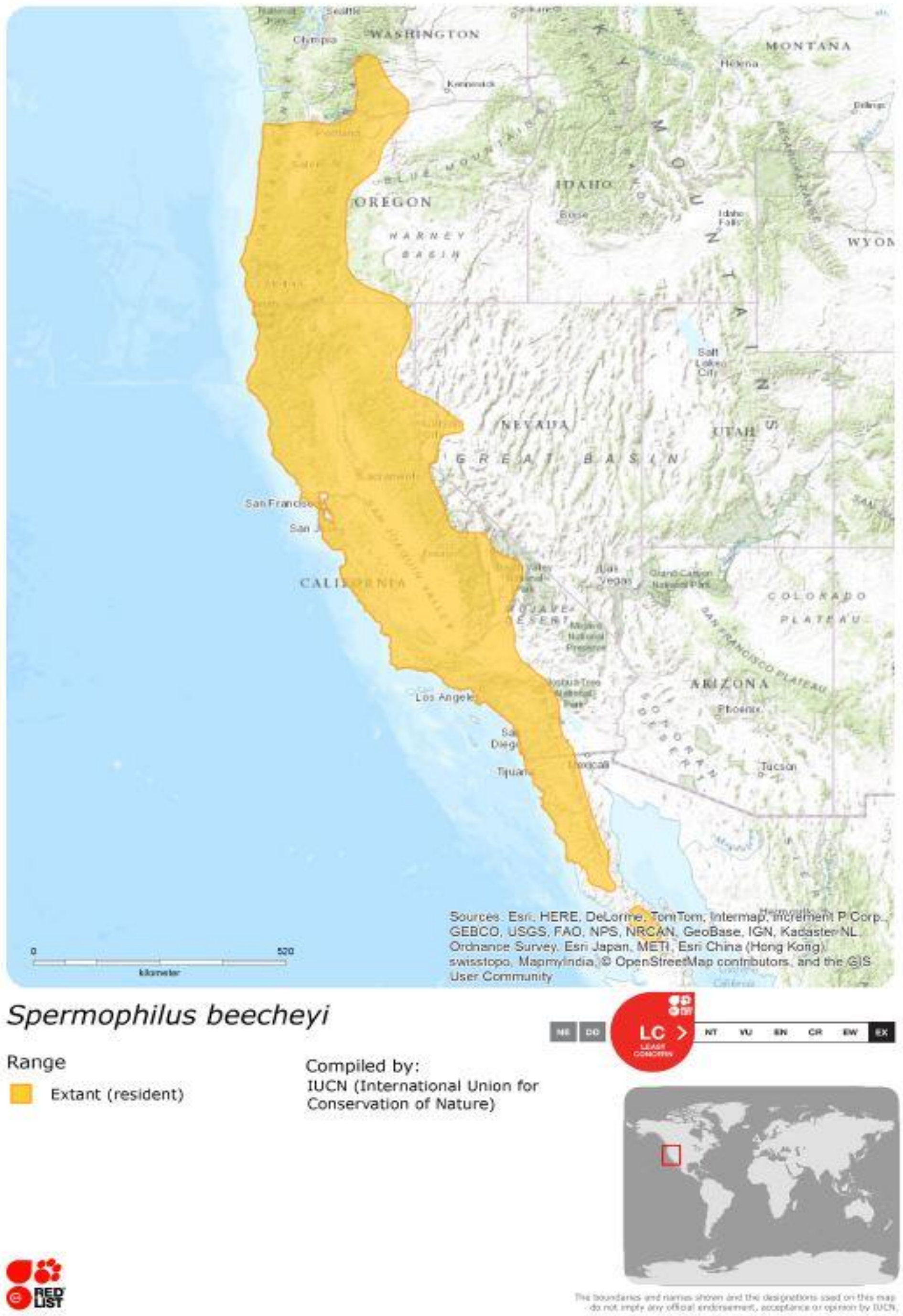


Figure 8 - Range of California ground squirrel. Source: Timm, Alvarez-Castaneda, and Lacher (2016).

3.1.1. California Ground Squirrel Life History

California ground squirrels, shown in Figure 9, are small to medium-sized mammals, ranging from 357 to 500mm in length and weighing 350 to 885g, with predominantly brown pelage and a gray mantel (Hubbart 2012). Individuals are relatively long-lived, living on average four years in the wild, females will produce 5 to 11 young per year, and colonies will often be comprised of several generations. Similar to their ability to occupy a diverse range of ecosystems, ground squirrels have a wide diet breadth which includes forbs, grasses, insects, berries, carrion, and in urban environments, garbage. Ground squirrels do not necessarily require open sources of water because their water intake occurs through the consumption of food with high water content. In the early season, grasses with high water content (e.g. 60 to 70 percent) are the primary food source in many grassland ecosystems, but during the dry season when grasses dry and lose water content, there is a shift to other types of food with a higher water content (e.g. insects) (Hubbart 2012, Lenihan 2007, Smith et al. 2016).

Figure 9 - California ground squirrel. Photo credit: Gary R. Zahm, U.S. Fish and Wildlife Service.

Ground squirrels are non-migratory and can have both independent burrow systems or colonies combined of several burrows with multiple entrances and families (Smith et al. 2016, Hubbart 2012). Home ranges for this species are centralized on single or colonies of burrows. Though some burrows have been documented to be less than $140m^2$, some studies have shown them to range from 300 to $900m^2$ and in some cases are as large as $5{,}000m^2$. Burrows can consist of several entrance points with tunnels spanning up to 40m, but average burrow length was found to be less than 10m. Entrances, as seen in Figure 10, are generally slightly elevated and serve as important monitoring points used by sentries to alert others of potential predator presence (Hubbart 2012). The construction of burrows and level of complexity is primarily related to the distribution of friable soils allowing easy development and maintenance of burrow structures.

Figure 10 - California ground squirrel and burrowing owl at a burrow complex. Source: Andrea Cruz, University of California, Davis.

3.1.2. Ground Squirrels at the Altamont Pass Wind Resource Area

Ground squirrel populations at the Altamont have been subject to several management regimes which have altered the distribution of this species that naturally would have been continuously distributed throughout the region (Smallwoord et al. 2009). The primary land use within the Altamont has been ranching and agriculture where landowners typically view ground squirrels as a pest species. This viewpoint has led to removal efforts at various intensities, ranging from no management to large scale continuous poisoning efforts. In addition to ranching and farming concerns, there are several wind farms in the region. Researchers have postulated that ground squirrel presence near turbines increases raptor use of these areas and results in higher collision risk (Smallwood and Thelander 2004, Smallwood et al. 2009, Hunt and Watson 2016).

Theories to reduce presence or visibility of ground squirrels near wind turbines have included moving commonly used structures (e.g. rock piles) away from wind turbines, maintaining taller grasses by excluding cattle, and implementing large-scale eradication to deter raptor use (Hubbart 2012, Schitoskey and Woodmansee 1978, Smallwood and Thelander 2004, Smallwood 2007). However, following a large-scale poison bait eradication effort in the Altamont, it was determined that the poison bait may have resulted in negative effects to non-target species via secondary exposure to toxins and reduction in ecosystem services (Hunt and Watson 2016). Research has determined ground squirrels are a keystone species within grassland ecosystems and that maintaining populations of ground squirrels is critical to ecological stability.

One of the more important roles ground squirrels play at the Altamont is they serve as the primary prey species for golden eagles (Hunt et al. 1999, Hunt 2002, Smallwood and Thelander 2004, Smallwood et al. 2009). In a dietary analysis conducted at the Altamont, where 339 dietary samples were analyzed, approximately 70 percent of the prey items were ground squirrels and represented approximately 65 percent of the biomass (Hunt et al. 1999). Behavioral studies at the Altamont have documented hunting behavior by golden eagles in close proximity to ground squirrel burrows (Smallwood et al. 2009). With an extreme population decline in the second most important prey species within the Altamont, black-tailed jackrabbit (*Lepus californicus*), reliance on ground squirrels for sustenance has likely increased.

Ground squirrel abundance studies at the Altamont have found the primary driving factor that influenced densities was the duration and level of control being implemented by landowners (Hunt 2002). Studies that evaluated ground squirrel habitat associations within the Altamont found that ground squirrel burrows typically occurred on the lower portion of the slope, there was an inverse relationship between elevation/slope and burrow density, and the majority of the burrows occurred in grass heights ranging 21 to 50cm tall (Smallwood et al. 2009). It was hypothesized that ground squirrels selected for these locations because of increased concealment provided by tall grass and lower slope positions. While notable patches of herbaceous vegetation have been documented at most burrows, it is likely that an optimal relationship between grass height and density exists, where vegetation is tall enough to provide concealment, while not inhibiting predator identification.

3.2. Methods

As previously discussed, several studies have evaluated ground squirrel abundance and distribution at the Altamont to assess potential relationships with foraging raptors (Hunt 2002, Smallwood et al. 2009, Hoover 2002). However, these studies were limited in their capacity to evaluate the relationship of ground squirrel distribution on golden eagle resource selection as they were constrained to smaller geographic regions in the Altamont and only had access to golden eagle point count data limiting inference (Hoover 2002). With improvements in species distribution modeling (SDM), it is now possible to overcome these limitations. The first step in analyzing the effect of ground squirrel distribution on non-adult golden eagle habitat selection is to develop an SDM for ground squirrels based on burrows to determine the potential distribution at the Altamont. The methods used to create this model are presented in the following subsections.

3.2.1. Ground Squirrel Data Collection

Burrow locations were collected using two methods within this study: points collected systematically as part of site-specific studies and points collected opportunistically while doing other surveys. The methodologies used to identify and mark burrow locations were part of larger studies published by Smallwood and Thelander (2004 and 2005) and Smallwood et al. (2009 and 2013). The remaining portion of the data set was opportunistically collected by Dr. Shawn Smallwood (Smallwood unpublished data 2007-2018). Within the published studies, there were three general approaches referred to here as “Vasco”, “turbine”, and “owl” methods. In all methods for burrow marking, points were recorded using a Trimble GPS receiver with sub-meter accuracy. Figure 11 shows the locations of the all burrow points collected.

In both turbine and Vasco methods, surveyors walked transects recording all burrows that had recent use (e.g. fresh grass within burrow). There were differences in transect distances and area surveyed between the turbine and Vasco methods. In the turbine method, transects were laid out 15 to 90m (at 15m intervals) from the turbine string at 70 turbine strings within the Altamont (Smallwood and Thelander 2004, Smallwood and Thelander 2005). In the Vasco method, transects were spaced 12 to 15m apart and incorporated 70 percent of the Vasco Caves Regional Preserve located in the northeastern region of the Altamont (Smallwood et al. 2009), regardless of turbine location. For the owl method, ground squirrel burrows were recorded opportunistically while surveying for burrowing owls from vantage points and walk over surveys (Smallwood et al. 2013, Smallwood unpublished data 2007 to 2018).

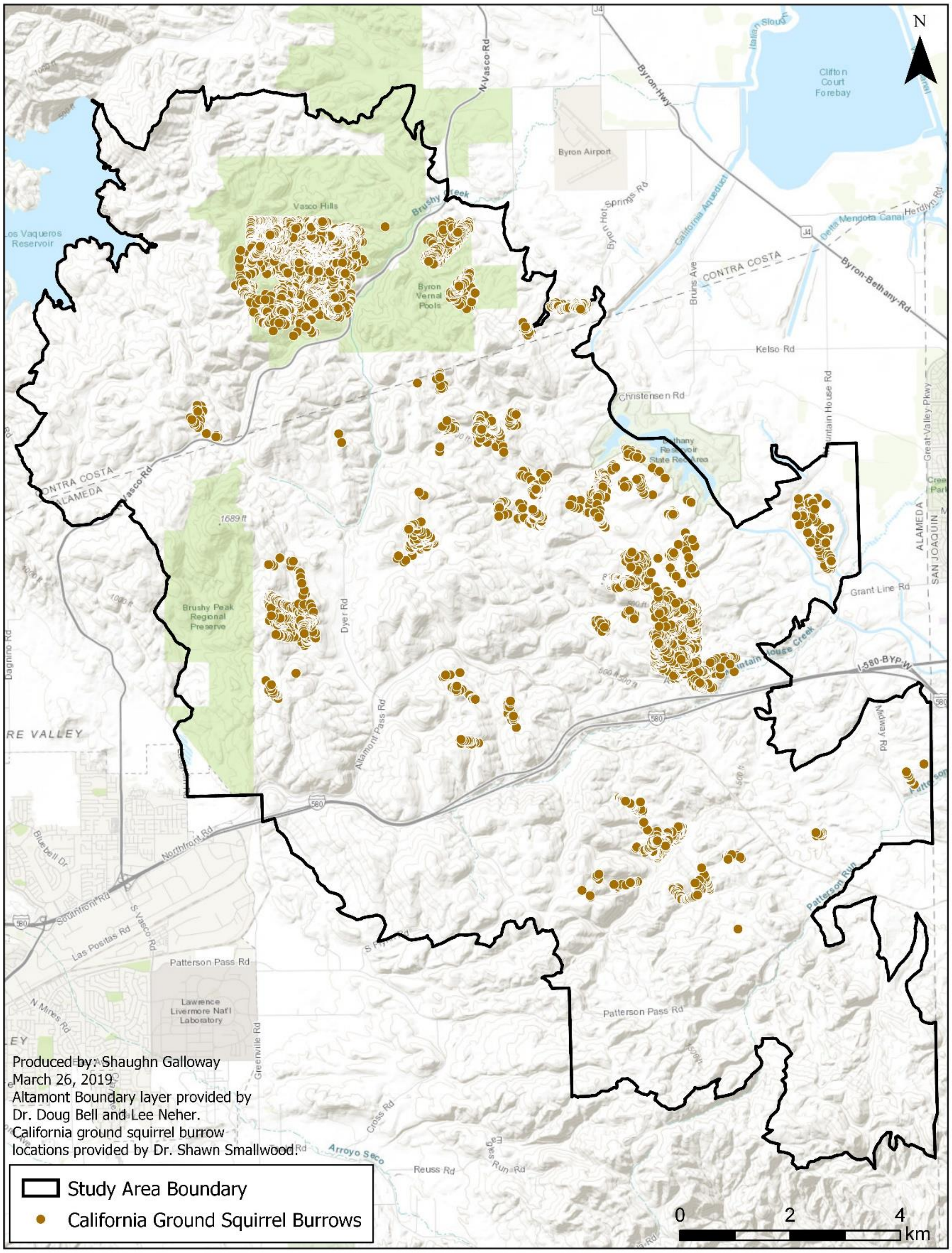


Figure 11 - California ground squirrel burrow locations. Data provided by Dr. Shawn Smallwood.

3.2.2. Environmental Variables for the SDM

The purpose of this analysis was to determine where ground squirrels might exist within the Altamont to serve as a proxy for potential prey distribution in the golden eagle model. Variables were selected based on the resource requirements necessary for individuals to breed, feed, and shelter outlined within the above sections. The variables considered in this analysis included elevation, slope, aspect, normalized difference in vegetation index (NDVI) (early and late season), soil type, slope position index (SPI), and vegetation type. These are listed in Table 2. In the following sections, additional information about each variable is provided, including purpose, origination, and processing steps.

Table 2 – Environmental variables evaluated for the ground squirrel SDM.

Variable	Data Type	Resolution	Source
Ground Squirrel Burrows	Point	<1m	Dr. Shawn Smallwood
Elevation	Raster	27m	USGS 3-DEP
Slope	Raster	30m	USGS 3-DEP
Aspect	Raster	30m	USGS 3-DEP
Normalized Difference in Vegetation Index	Raster	30m	Climate Engine
Soils	Raster	30m	NRCS and Esri
Slope Position Index	Raster	30m	USGS 3-DEP and Dr. Tom Diltz University of Nevada, Reno
Land Cover	Raster	30m	USGS LANDFIRE

In general, data for each variable was downloaded and projected into NAD 1983 UTM Zone 10N. Once downloaded, all layers were clipped to the study area. Maxent requires all cells within the variables to be aligned and this was accomplished during the clipping phase using the "Snap to Raster" setting. The following subsections discuss additional processing steps taken for each variable.

3.2.2.1. Elevation, Slope, and Aspect

In previous publications, it was shown that ground squirrel burrow distribution was affected by both elevation and slope (Smallwood et al. 2009). Burrows were typically associated with lower elevations and flatter slopes. Individuals likely selected for these locations because they may be less visible to predators, aid in predator detection, and improve proximity to food due to better growing conditions in these locations (Leger, Owings, and Coss 1983, Smallwood et al. 2009). Although there is no documentation of the effect of aspect on burrow locations, it was included as a candidate variable in this analysis. Aspect may influence growing conditions and water retention (e.g. some aspects receive less sun exposure), and/or it is possible that some aspects are not as heavily used by predators.

Elevation, slope, and aspect variables were generated from a digital elevation model (DEM) downloaded from the USGS's 3DEP program (U.S. Geological Survey 2017a). The resolution of the DEM was one arc-second, equating to approximately $27m^2$. The DEM was then converted to 30m resolution using bilinear interpolation, matching the resolution of the other variables. Slope and aspect in degrees were calculated using the corrected DEM. The aspect layer ranged from 0 to 360°, with both 0° and 360° representing north, therefore further processing was required before it could be used for analysis. Aspect was reclassified into four categories representing north (0 to 45° and 315 to 360°), south (135 to 225°), east (46 to 134°), and west (226 to 315°).

3.2.2.2. Normalized Difference in Vegetation Index (NDVI)

As discussed in Section 3.1.1, ground squirrels do not rely on open sources of water but obtain approximately 90 percent of their water from their food (Hubbart 2012). In burrow studies at the Altamont, Smallwood et al. (2009) had documented that several ground squirrel burrow locations had distinct patches of healthy vegetation that differed from the surrounding landscape. The growing season for annual grasses occurs in the wet season spanning January through March, and grasses begin to senesce or go dormant by June. Because ground squirrels are non-migratory, and grasses provide concealment from predators and are a critical food source, it is likely that ground squirrels are selecting patches that have healthy grasses for the greatest proportion of the year.

There are several ways to quantify vegetation health using remote sensing techniques, including greenness, wetness, and Normalized Difference in Vegetation Index (NDVI) (Cohen and Goward 2004). There are pros and cons to each classification methodology, however, NDVI has been widely accepted as a reliable measure of vegetation quality or health (Fraser et al. 2011). NDVI uses the differences in red and near-infrared (NIR) spectrum to assess plant health and is calculated using Equation 2 (Cohen and Goward 2004).

$$NDVI = (NIR - Red)/(NIR + Red) \tag{2}$$

Vegetation health was measured at two annual time points representing early season vegetation health (February to March) to coincide with initial growth, and late season vegetation health (June to July) to capture vegetation senescence (Figure 12). Surveys for ground squirrel burrows occurred across several years (1999 to 2018) which included both wet and dry years, including two periods of prolonged drought (Smallwood, Neher, and Bell 2017). Imagery from Landsat, downloaded using Climate Engine, was used to calculate NDVI for the study area. To compensate for the interannual variation in vegetation patterns, NDVI layers were downloaded for each survey year and the average NDVI for the study area was calculated for both early and late season NDVI (Huntington et al. 2017).

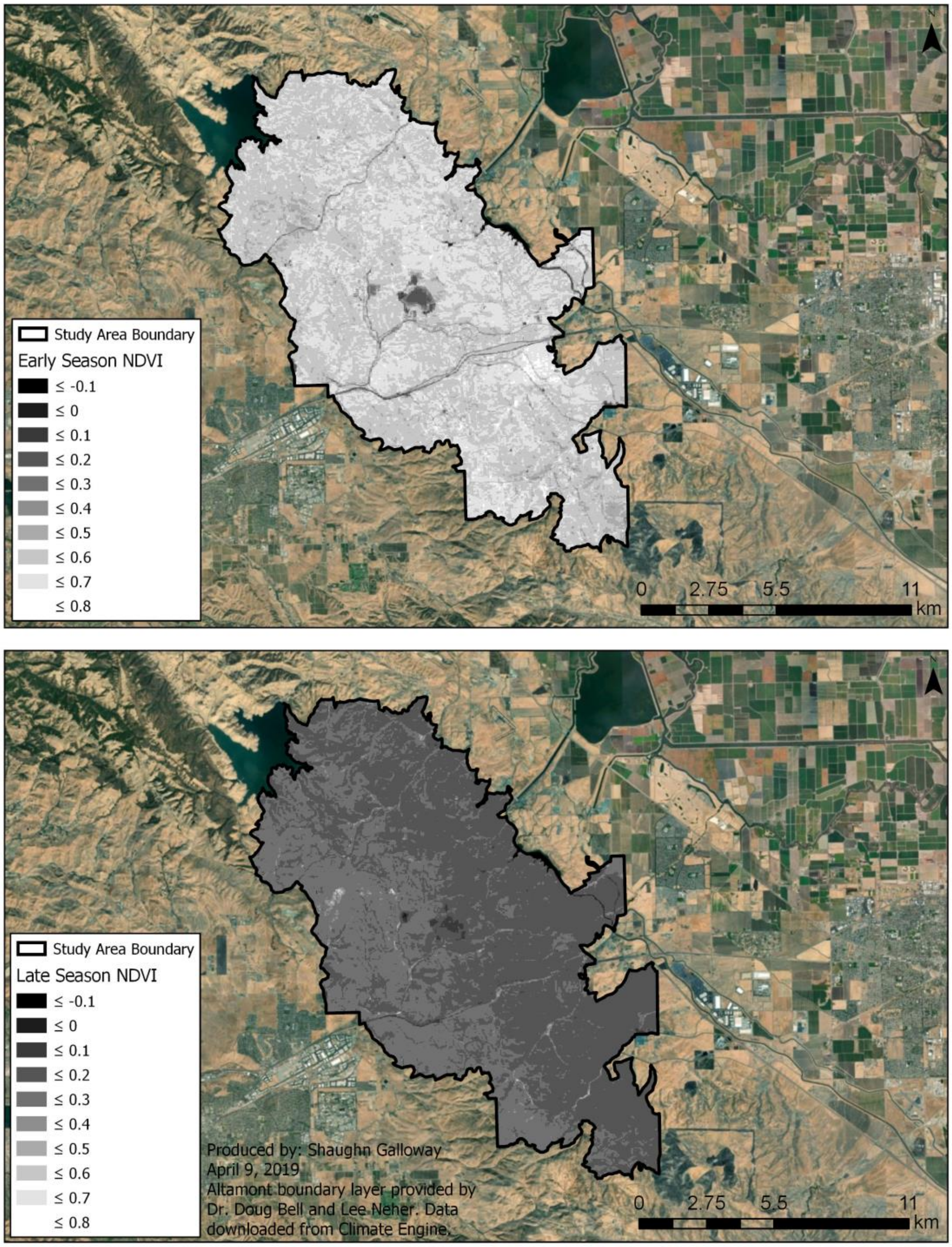


Figure 12 - Differences in vegetation health between early and late season NDVI variables. Data downloaded from Climate Engine.

3.2.2.3. Vegetation and Soil Type

In addition to vegetation health, landcover type likely influenced where ground squirrel burrows were located which may reflect individual preferences for specific plant communities or avoidance of disturbed areas. To get the distribution of land cover types within the study area, the Existing Vegetation Type (EVT) layer was downloaded from the USGS LANDFIRE program (U.S. Geological Survey 2017b). Vegetation classification is based on imagery collected from 2013 to 2017, with preference given to 2016, and was in 30m resolution. The EVT layer contained 15 landcover types.

Burrow systems are limited to specific soil textures, those possessing friable characteristics which are often referred to as "single grain", meaning largely absent of large particulates and having a soft or weak consistency (Jahn et al. 2006). Soils that contain friable characteristics are sandy, silty, or loamy soil textures generally having a lower clay component. The nature of these soil textures allows for easy manipulation and congealment when compacted, making ideal conditions for burrow systems (Hubbart 2012).

The National Resource Conservation Service (NRCS) has collected soil data across the United States and has made this data available for use in both spatial and tabular formats (Soil Survey Staff NRCS, 2017). The NRCS SSURGO Downloader was developed by NRCS to make these data available in a spatial format. Soils layers were downloaded from the SSURGO Downloader for Alameda and Contra Costa counties. The soil layers were merged together. Within the soil layer, the attribute "Particle Size" was used to identify soil textures which would have friable attributes. There was a total of ten particle sizes within the layer.

3.2.2.4. Topographic/Slope Position Index

In their field research, Smallwood et al. (2009) found that ground squirrel burrow distribution varied by slope and elevation, where more burrows occurred on flatter slopes and lower elevations. However, it is possible that the relative position on the topographic features is more important than actual slope or elevational value. While elevation and slope data provide useful information about topography generally, they do not identify where each location occurs on the topographic features (e.g. top or bottom of a hill). One way that has been proposed within the literature to determine slope position is to use a two-step process which included calculating topographic position index (TPI) and slope position index (SPI) (Weiss 2001).

Topographic position index was calculated by applying focal statistics to each point (or cell) to determine first the average elevation of pixels in a defined search neighborhood around it (Weiss 2001). Then the focal mean value for the neighborhood was subtracted from the center point or cell. When the value at the center point was positive, it was considered part of a "ridge" and when negative was considered a "valley." However, these TPI values were not comparable between differing search neighborhoods as they are not a standardized index.

Slope position index standardizes TPI, using standard deviation and slope degree so that outputs can be directly compared between search neighborhoods and provides more information about the location of each cell. The resulting output from SPI can be classified into six different classes using standard deviations from the TPI output: Valley (< -1 stdev), Low Slope (≥ -1 to < -0.5 stdev), Flat (-0.5 ≥ to ≤ 0.5 stdev, slope ≤ 5°), Mid Slope (-0.5 ≥ to ≤ 0.5 stdev, slope ≥ 5°), Upper Slope (> 0.5 to ≤ 1.0 stdev), and Ridge (> 1 stdev). In general, each of these classes refers to whether or not the slope exhibits concave or convex properties can be thought of as a sigmoidal curve.

This analysis used the Topography Toolbox for ArcGIS 10.x developed by Dr. Tom Diltz (2015), to calculate SPI for the study area (Figure 13). There was not a standard protocol for establishing the search neighborhood as it is highly project-specific depending on the elevation range and resolution of the elevation data (Weiss 2001). The maximum elevation within the study area was approximately 650m and the resolution of the DEM was 30m. To find an adequate neighborhood size, several TPI layers were created from 3x3 cell to 10x10 cell neighborhoods and standardized using SPI. Slope degrees > 2° were used to differentiate Mid-slope and Flat classes (Diltz 2015). All SPI layers were evaluated to determine how well each layer represented the study area. The larger search radii resulted in the oversimplification of the study areas terrain so the 3x3 cell search radius was selected for this analysis (Figure 13).

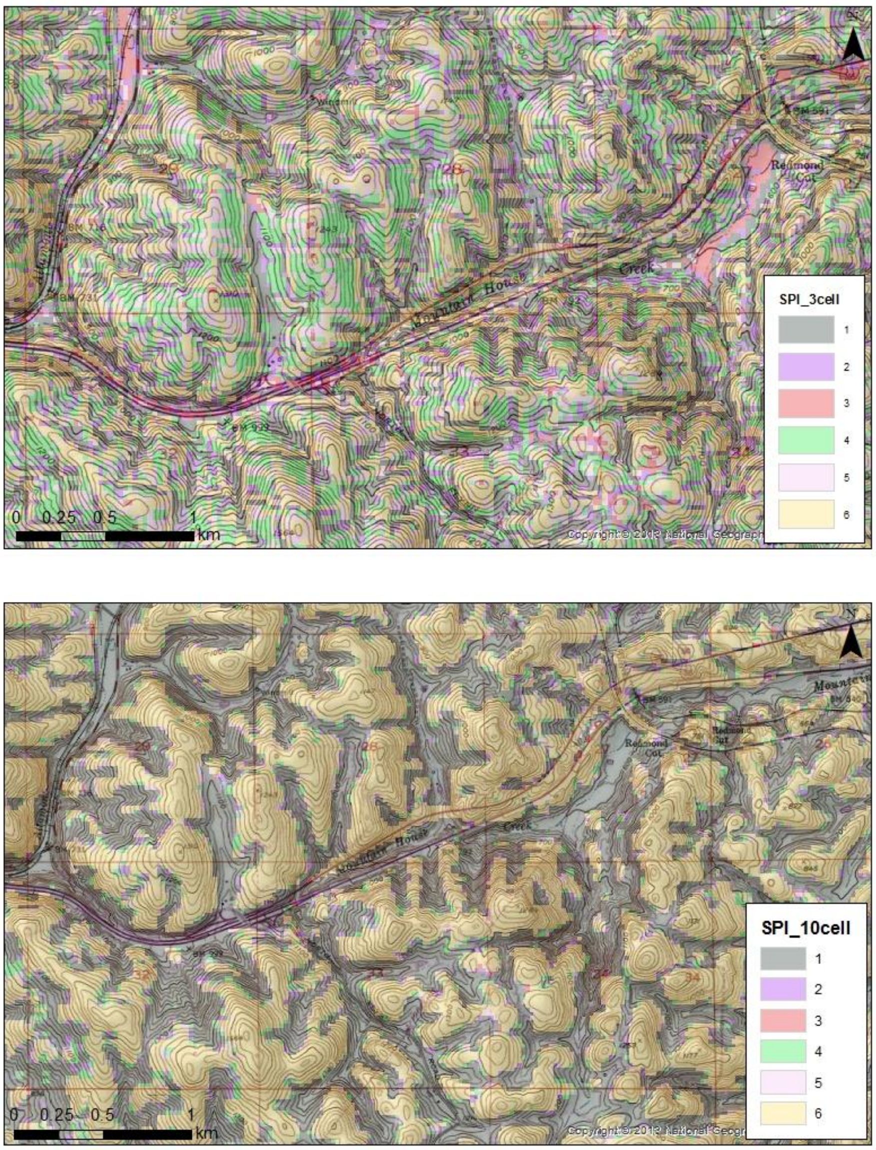


Figure 13 – Difference in slope position index classes comparing 3x3 and 10x10 cell search neighborhoods. Larger search radii resulted in reduced identification of slope positions. Slope position index values; 1 = Valley, 2 = Low Slope, 3 = Flat, 4 = Mid Slope, 5 = Upper Slope, and 6 = Ridge.

3.2.3. Data Exploration

The maximum entropy modeling technique shares similar assumptions as several other presence-only modeling techniques (Yackulic et al. 2013). These assumptions include 1) that detection probability is constant across the study area and 2) random or at a minimum representative sampling of the study area. In addition to these assumptions, variables should not exhibit collinearity as these effects can overstate the effect of the variables and overfit the model (Merow, Smith, and Silander 2013).

The first assumption influences the predictive capacity of the model. When this assumption is not met, the resulting prediction surface can only be interpreted as a relative occurrence rate (Yackulic et al. 2013, Merow, Smith, and Silander 2013). The violation of the first assumption and use of relative occurrence rate is common in wildlife studies using presence-only data. While results are not true probability, they provide a measure of habitat suitability for the species. The flexibility of the second assumption largely depends on the study area of interest. If the presence samples are representative of the study area and the variables used in the modeling process, other researchers have shown that this assumption can be loosely met.

Variables were assessed for collinearity using a Pearson's correlation coefficient. Variables were considered colinear if the coefficient was > 0.6 (R Core Team 2017). Based on this analysis, none of the variables were colinear. Because the ground squirrel burrow data was sporadically collected it was not possible to calculate a detection probability, which violated the first assumption and required the output to be interpreted as relative occurrence rate. To test for the meeting of the second assumption, histograms and other graphs were created for each variable to evaluate the range of the variable within the study area. The results of this analysis are provided below.

3.2.3.1. Elevation, Slope, and Aspect

The elevation in the study area varies by approximately 650m, where the highest points occur along the southwestern boundary. As discussed in Section 3.2.1, ground squirrel burrows were collected using several different methods (e.g. Vasco, turbine, and owl). A series of histograms were used to evaluate the distribution of burrow locations within the study area. Burrows distribution ranged from approximately 45 to 400m elevation (Figure 14, Figure 15, and Figure 16). In Figure 14, the burrow locations range from 47 to 391m and in Figure 15 burrows range from 103 to 297m in elevation. While the distribution of the burrows does not cover the entire elevational range of the study area, it was determined this dataset was satisfactory for analysis based on the elevational ranges covered by the entire burrow dataset. This conclusion was made because the difference in elevation was minimal (e.g. 200m) and the locations within the study area at the unrepresented elevations are limited in extent.

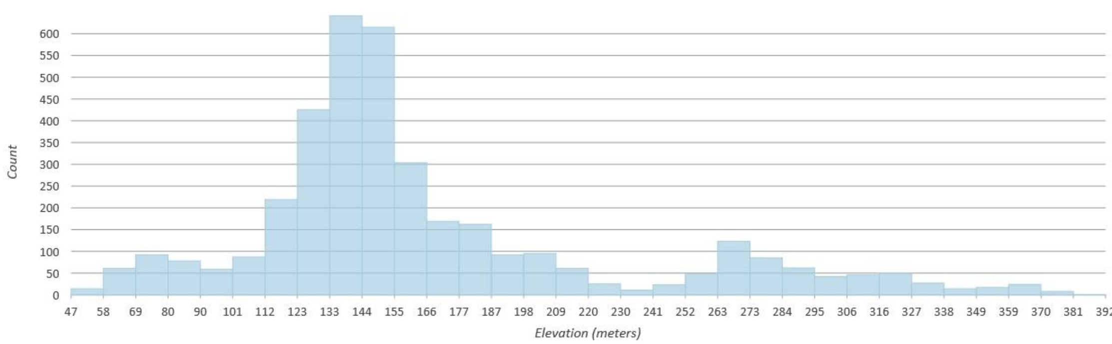


Figure 14 – Count of burrows that were collected during turbine specific and opportunistic surveys plotted by elevation.

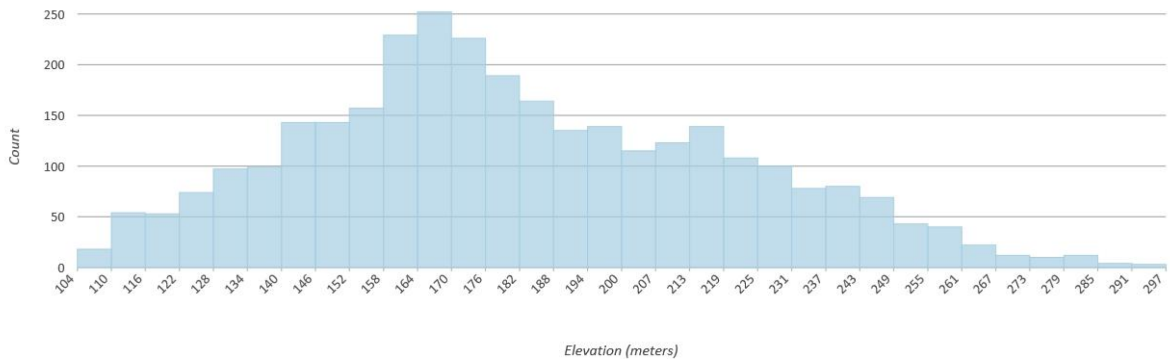


Figure 15 – Count of burrows that were collected during Vasco Caves surveys plotted by elevation.

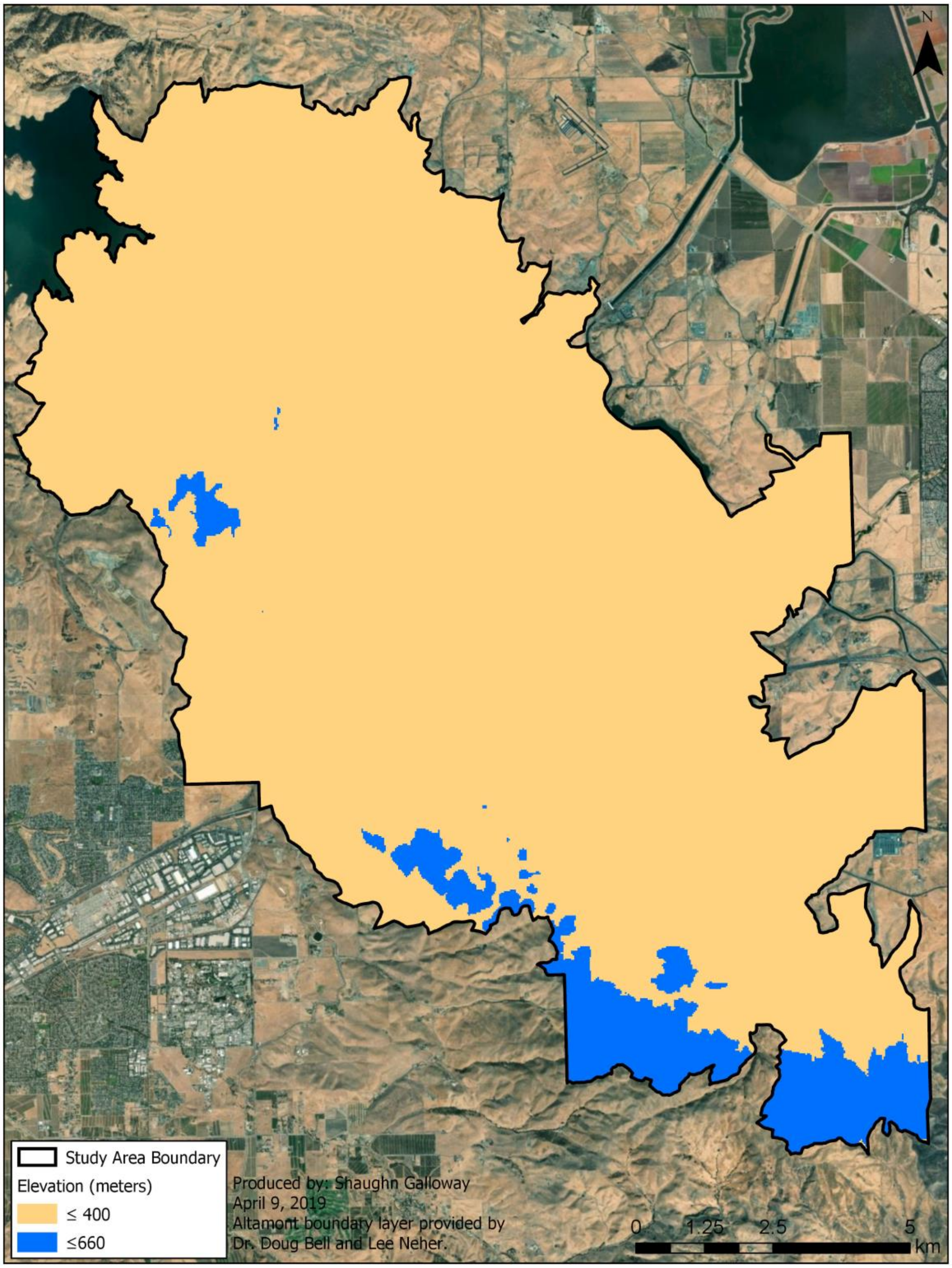


Figure 16 - Spatial distribution of elevation that were not represented by the ground squirrel burrow locations. Tan represents the area with elevations represented by the burrow data set and blue indicates areas with elevations not represented by the burrows data.

Slope angles in the Altamont range from 0 to 40°, with the steeper slopes occurring around the Brushy Peak area, along roadways, and the rockier more rugged southeastern portions of the study area. To explore the distribution of slope within the burrow data, a histogram was used. Burrows were distributed on slopes with angles from 0 to 30° within the wind resource area (Figure 17). While the distribution of the burrows does not cover the entire slope range of the study area, it was determined this dataset was satisfactory for analysis. This conclusion was made because the difference in slope was minimal (e.g. 10°) and the locations within the study area at the unrepresented slope angles are limited in extent (Figure 18).

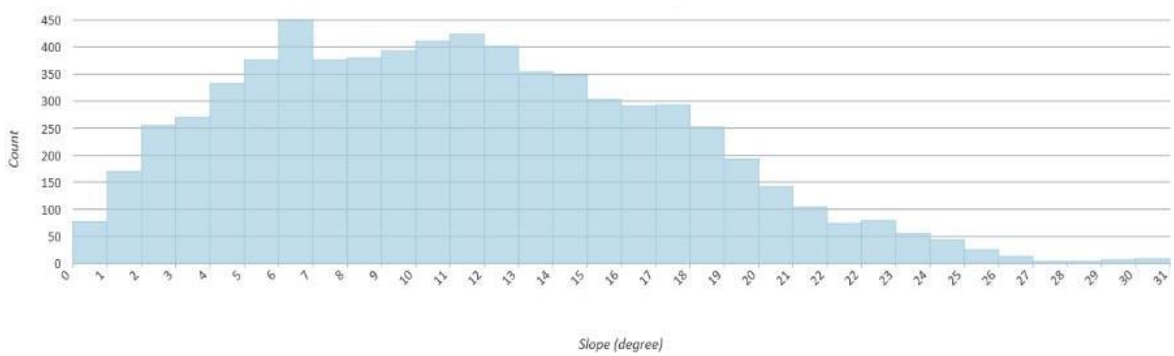


Figure 17 – Histogram of ground squirrel burrow distribution by slope degree.

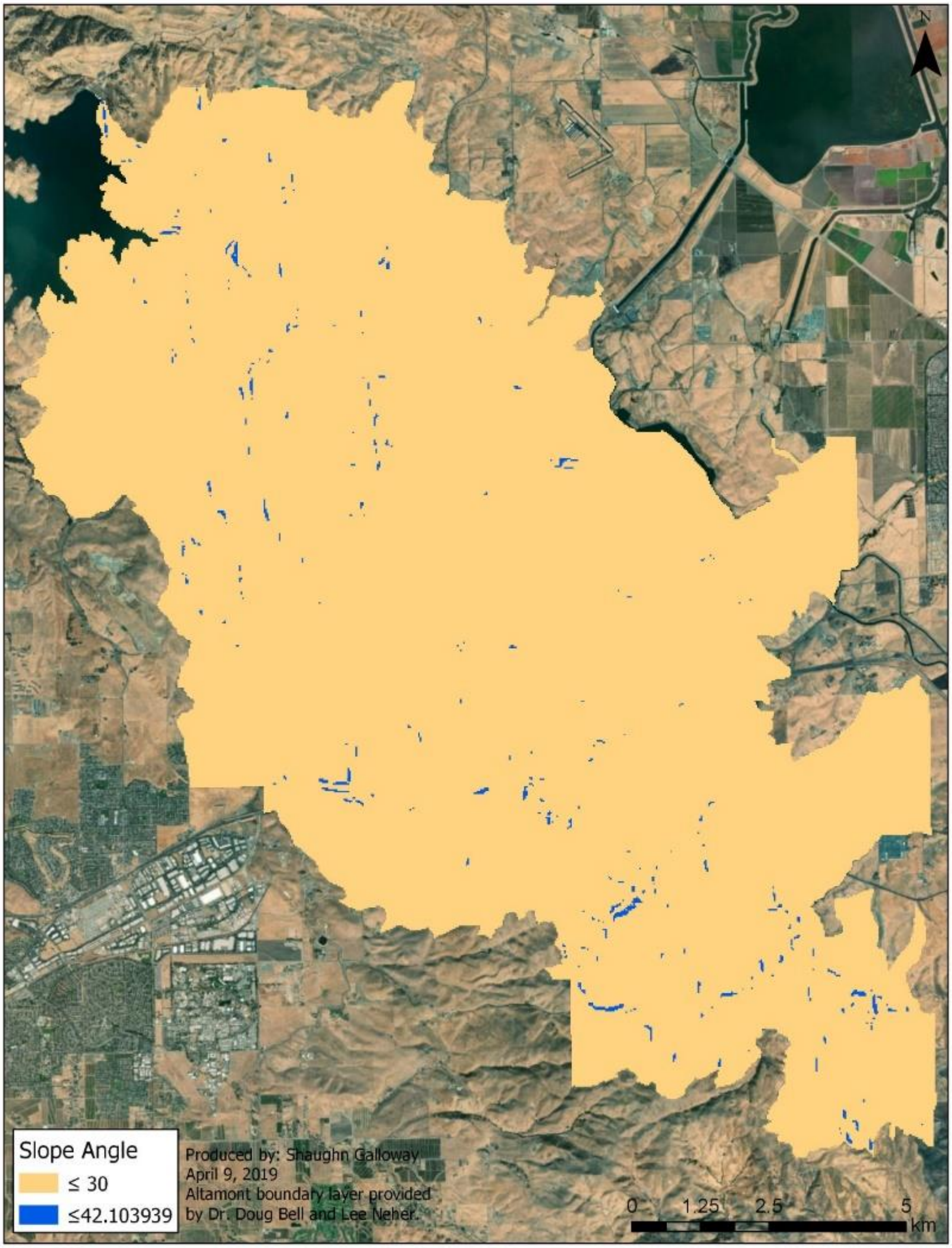


Figure 18 - Spatial distribution of slope angles represented by the ground squirrel burrow data. Tan indicates the areas with slope angles included in the burrow data set and blue indicates locations not represented by the data.

The majority of the topographic ridges within the Altamont trend in a northwest/southeast direction (Figure 19). A bar chart was used to evaluate the distribution of burrow within aspect categories (Figure 20). As far as aspect is concerned, burrows were well distributed across all categories, with a marginally higher number within the east category. Based on the distribution pattern of burrows within each aspect category, it was determined that the burrows occurred on all aspects within the study area and therefore, met the second assumption.

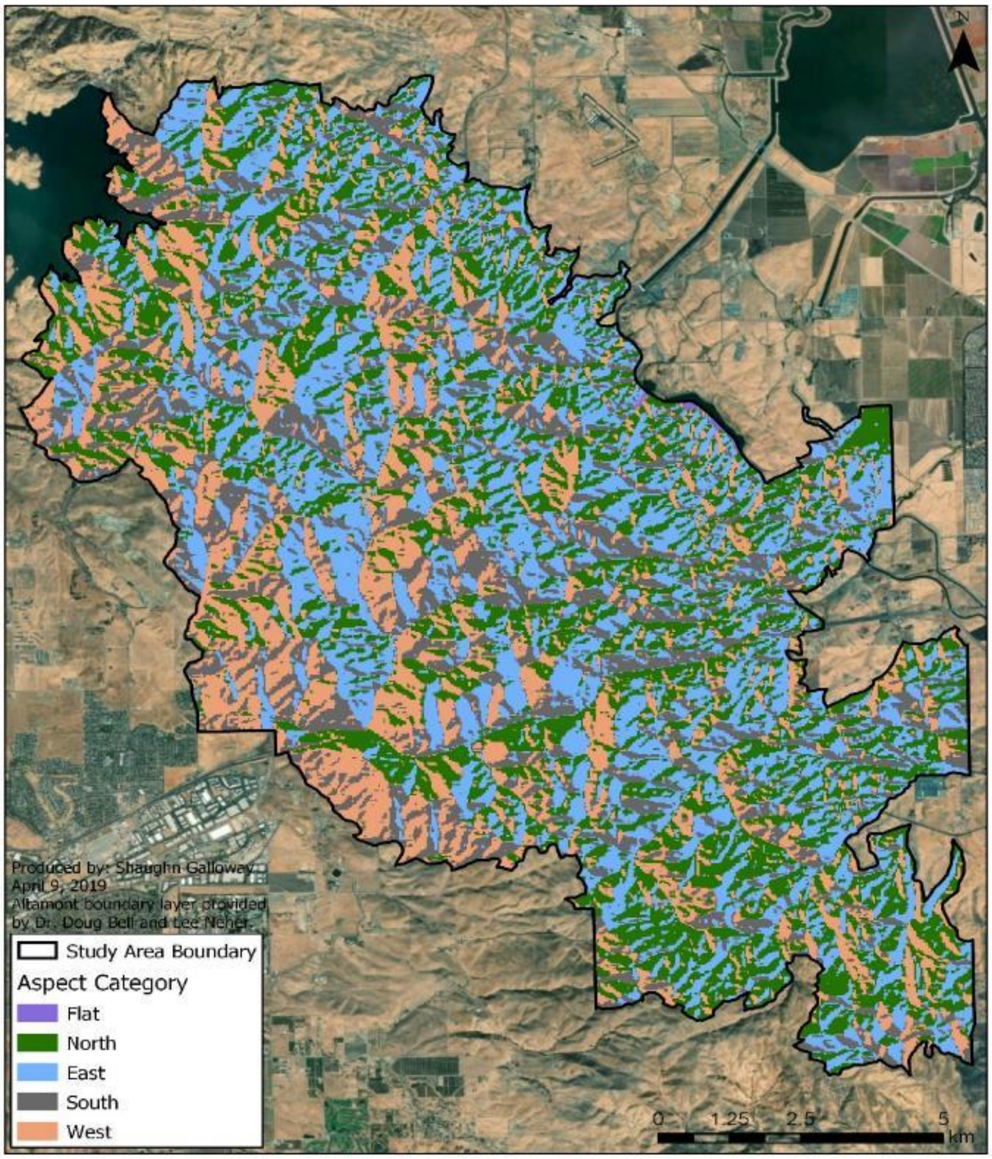


Figure 19 - Aspect categories within the study area.

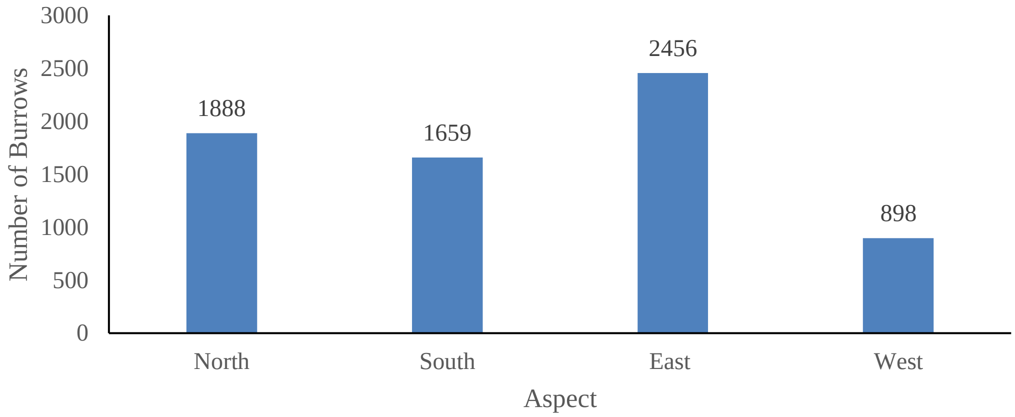


Figure 20 - Number of burrows by aspect category.

3.2.3.2. Normalized Difference in Vegetation Index

For this analysis two NDVI variables were created representing wet and dry seasons, referred to as early season and late season NDVI. Values for NDVI range between approximately 0 to 1, with higher values indicating healthy vegetation. Across the study area, early season NDVI values ranged from approximately 0 to 0.75 and late season NDVI values ranged from 0 to 0.67 (see Figure 12 above). Histograms were used to assess the distribution of NDVI values across all ground squirrel burrows. Early season NDVI values across all burrows ranged from approximately 0 to 0.7 and late season NDVI values across all burrows ranged 0 to 0.4 (Figure 21 and Figure 22).

Despite the burrow distribution not representing the full range of values within the late season NDVI variable, this variable was believed to be suitable for analysis. Vegetation within the Altamont associated with higher late season NDVI values existed along persistent water sources and oak woodland environments (Figure 23). These features are not necessarily important habitat components for the species as they do not require open water sources (e.g. most water comes from food) and healthy vegetation represented by oak woodlands is not necessarily important to ground squirrels. Additionally, these areas were limited in distribution, occurring rarely only as small patches within the Altamont. Thus, it was concluded that these variables were adequate for further analysis.

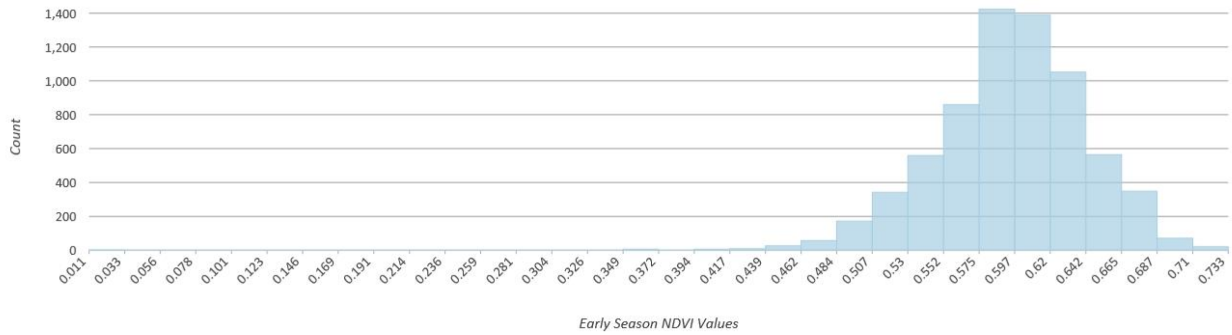


Figure 21 - Distribution of all ground squirrel burrows by early season NDVI values.

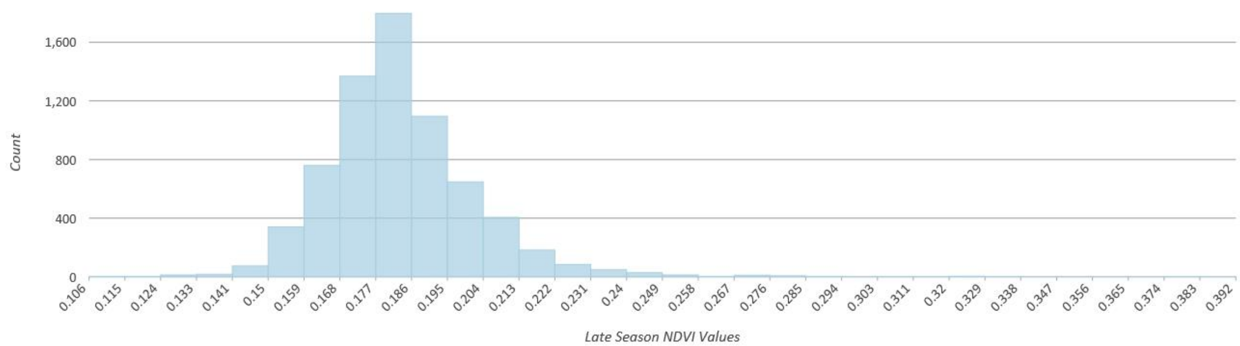


Figure 22 - Distribution of all ground squirrel burrows by late season NDVI values.

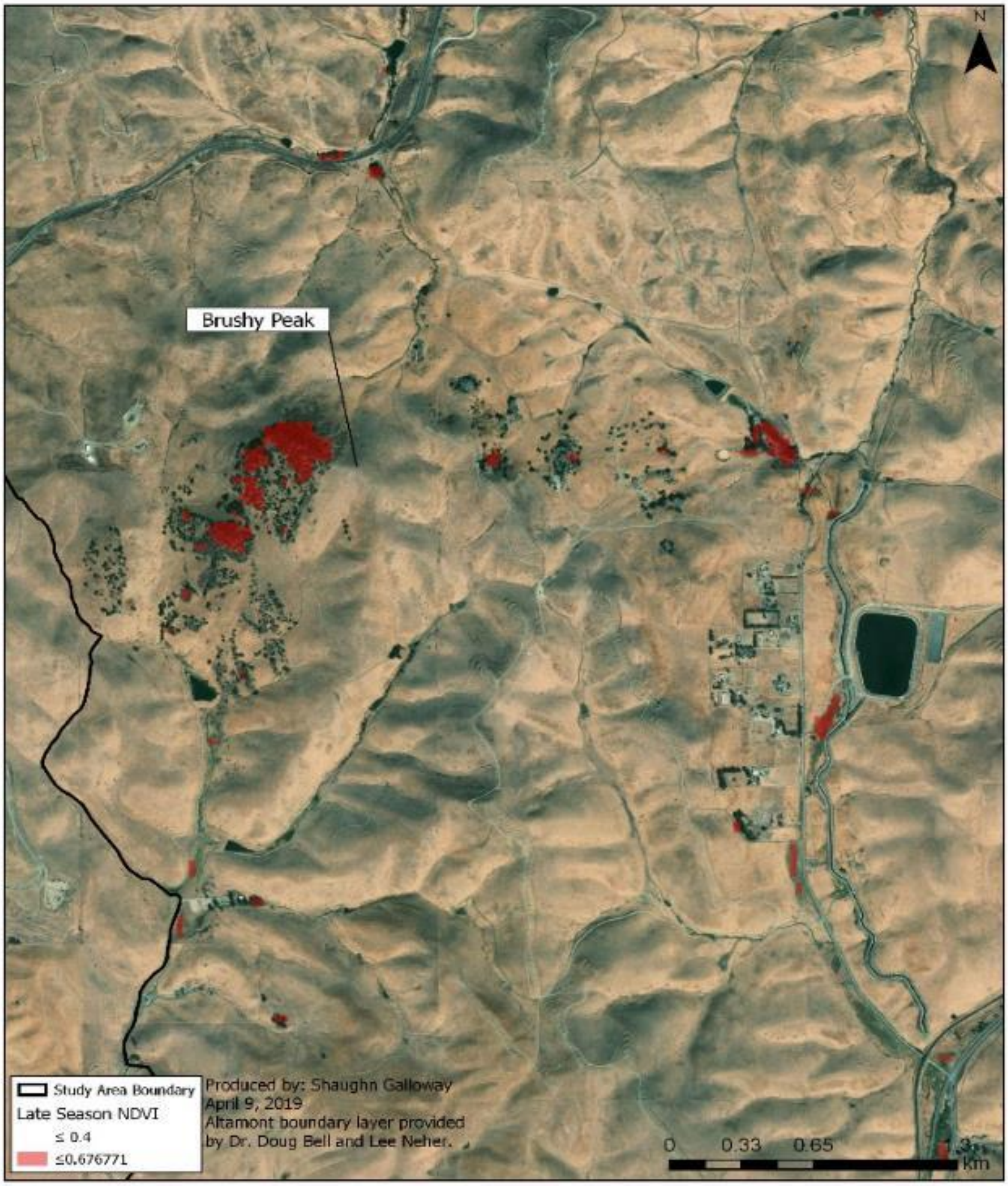


Figure 23 - Close-up showing where high late-season NDVI values occur only within the forested areas and areas with persistent water.

3.2.3.3. Vegetation and Soil Texture

Within the study area, there were eight different vegetation classes and six soil texture classes. There were two analytical techniques used to determine if they met the second assumption: a bar chart of occurrence rate (raw counts) and used-available analysis. This analysis was used to determine if burrows were occurring in the lesser distributed habitat types at a representative rate.

Based on the bar chart for vegetation, it was concluded that burrows were not occurring representatively in all vegetation classes. As Figure 24 shows, 90 percent of the burrows occurred within the “California Annual Grassland” category and other classes were under-represented. After evaluating the Used/Available (UA) chart, the only two categories that were used greater than available were “California Annual Grassland” and “California Mesic Chaparral.” For this reason, it was determined that this variable was not suitable for analysis because the burrow data does not adequately reflect the complete environmental domain of the study area.

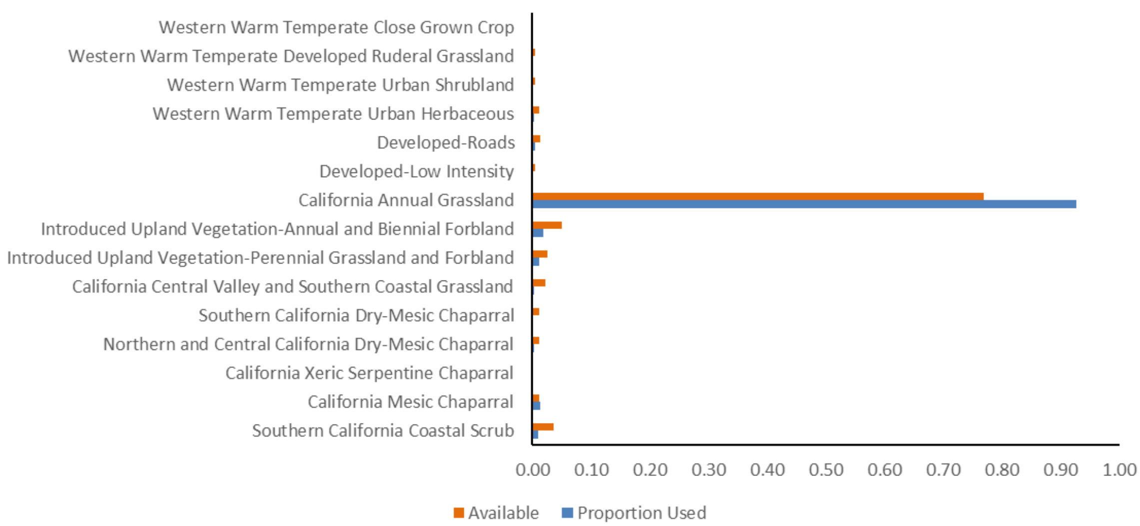


Figure 24 – Evaluation of the proportion of vegetation types available within the study area, compared to the proportion of ground squirrel burrows within each category.

As expected, the soil bar chart (Figure 25) indicated that burrows were only in classes which could support burrow systems via friable soil characteristics. Within the study area, some soil textures were not abundant and as a result not used (e.g. “Coarse-Loamy”). Considering the used-available chart, within the classes that would be capable of supporting burrow structures, the numbers of burrow points were similar to the level of availability; some cases more and some cases fewer, but at least to the degree that it was concluded that the distribution of burrows can accurately represent the conditions within the study area.

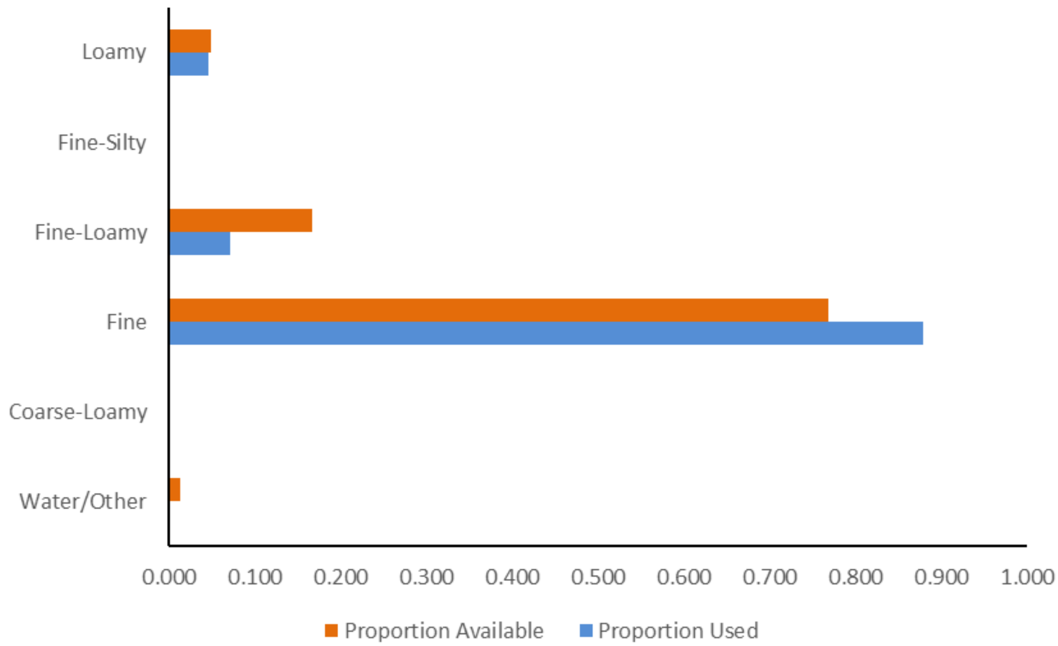


Figure 25 – Evaluation of the proportion of soil textural classes available within the study area, compared to the proportion of ground squirrel burrows within each category.

3.2.3.4. Slope Position Index

The study area predominately consisted of the Ridge and Valley slope position index categories, as shown in Figure 26. A UA analysis was conducted to determine if the distribution of ground squirrel burrows adequately represented the study area. By comparing the number of burrows by slope position category, it is evident that that slope position was adequately represented in the study area (Figure 27). Based on these results, the burrow data distribution adequately represents the SPI categories within the study area, thus it was determined this variable is suitable for analysis.

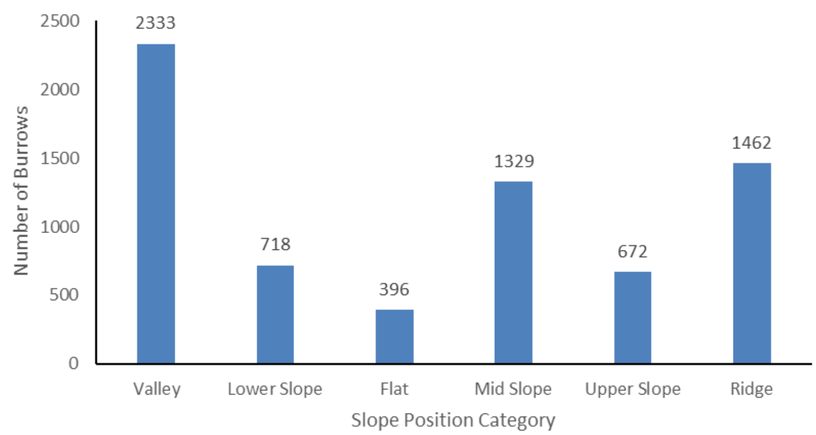


Figure 26 - Number of burrows within each slope position category.

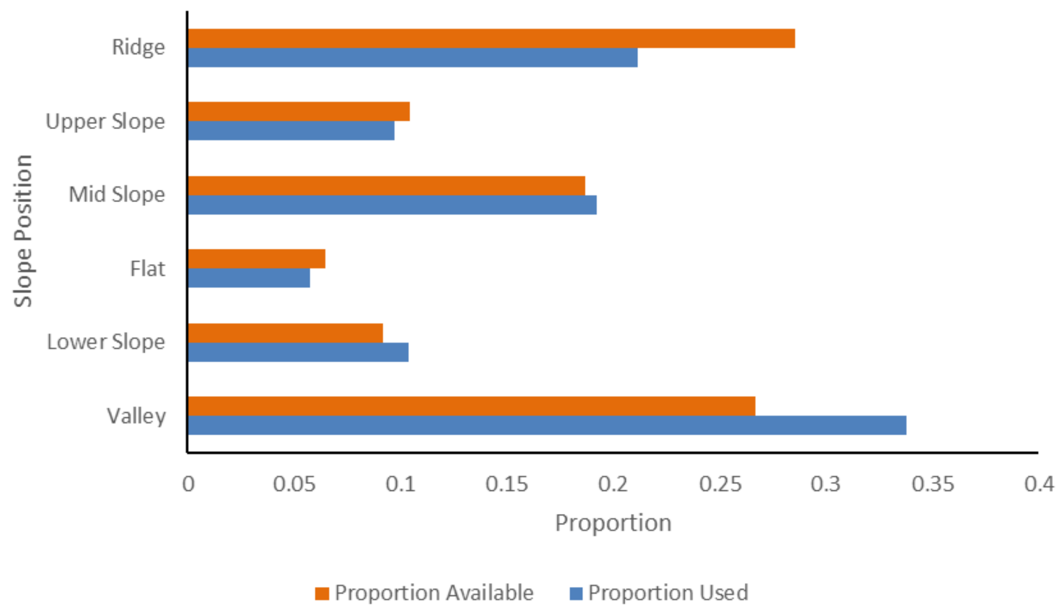


Figure 27 – Evaluation of the proportion of slope position types available within the study area, compared to the proportion of ground squirrel burrows within each category.

3.2.3.5. Summary

Due to the various survey methods used to collect burrow locations, it was not possible to meet the first assumption of presence-only modeling. Therefore, model results are interpreted as relative occurrence rate. Of the initial variables considered for further analysis, most of them were able to satisfy the second assumption for presence-only modeling. In the cases of elevation, slope, and late season NDVI, not all values were represented by presence points, but as discussed above were satisfactory for analysis. One variable that did not satisfy the underlying model assumptions was vegetation type, and as a result, was not used in the modeling process. The variables carried forward into the analysis included early/late season NDVI, Aspect, Slope, Elevation, SPI, and Soil type because they met the model assumptions.

3.2.4. Modeling Environment

The Maxent program provides great flexibility for choosing model settings. These model settings can have various impacts on model outcomes but vary in importance (Merow, Smith, and Silander 2013, Baldwin 2009). The most important settings include the number of background points, selecting feature classes, regularization multiplier value, replicate run type, convergence iterations, using a bias file, and an output type. Each of these settings represents a critical decision about how the covariate surface is defined, which mathematical relationships will be used, how models are fit, and how each model can be evaluated. These settings are located in the main interface, basic, advanced, and experimental setting pages within the Java program.

Ground squirrel burrow locations were exported to an Excel comma separated values (.csv) file and environmental variables were converted to American Standard Code for Information Interchange (ASCII) and opened in the Maxent program (Figure 28). Variables were set as either continuous or categorical using the drop-down menus. Maxent offers four output types which included raw, logistic, cloglog, and cumulative. For this analysis, the logistic output was selected because this output type standardizes predictions from 0 to 1. While raw outputs have been preferred by some researchers, this approximately 40,000ac study area at 30m cell resolution would create unintelligible outputs because all cells add to one (Phillips et al. 2017, Merow, Smith, and Silander 2013). Additionally, while the cumulative output has been described as useful to define a species range, this is not the intent of the study. Recently, cloglog has been shown to be roughly equivalent to logistic outputs but was ultimately eliminated here because of uncertainty in performance associated with large datasets and potential for overfitting of the model (Phillips et al. 2017).

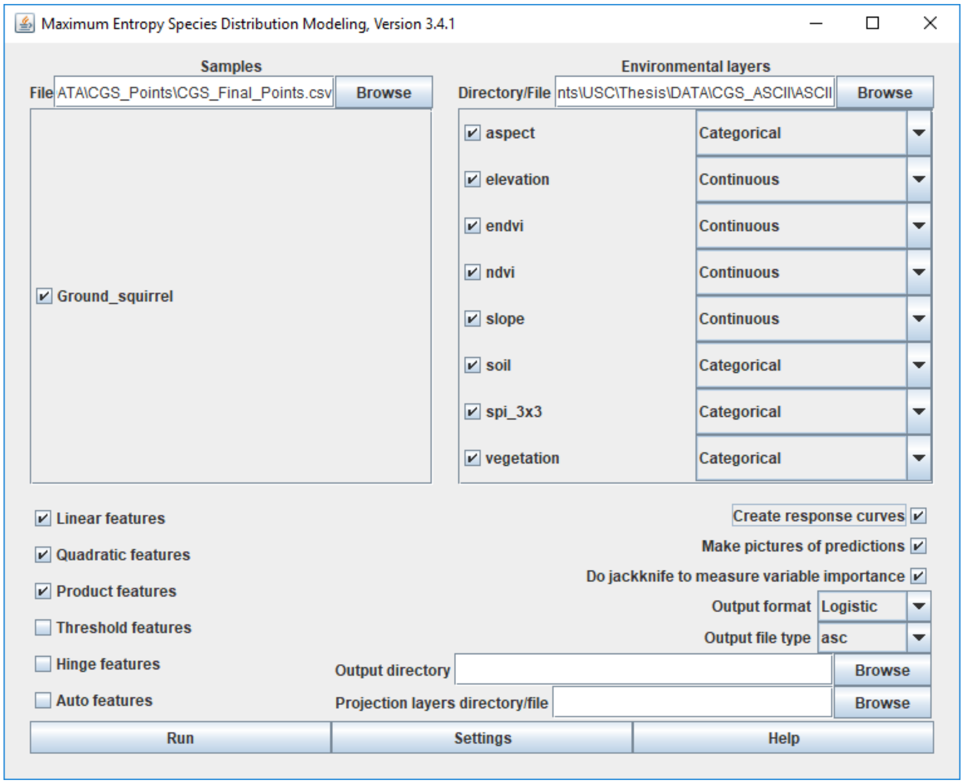


Figure 28 - Maxent main interface example settings.

Maxent allows for selection of features which define the mathematical relationship used to fit the covariate background surface. Default features settings include linear, quadratic (square of variable), product (product of two variables), and hinge (categorical variable as binary) feature classes (Phillips, Anderson, and Schapire 2006). Depending on the number of presence locations, Maxent will try to fit more complex relationships to improve model fit. However, using the default settings may overfit the model by fitting relationships that are not biologically meaningful to the species (Merow, Smith, and Silander 2013). This analysis used linear, quadratic, and product feature classes, because there were no biologically significant reasons to include threshold (continuous variable converted to binary) and hinge feature classes.

Setting the number of background points is an important step because they contrast against the presence points to determine important environmental characteristics (Merow, Smith, and Sildander 2013). There is no recommendation in the literature for the total number of background points to use for SDMs. However, the total number of points should be enough to adequately represent the environmental characteristics in the study area; defining the environmental domain (Merow, Smith, and Silander 2013, Koper and Manseau 2010, Barbet-Massin et al. 2012). Typically, background points are chosen at a multiple of 2 to 10 times the amount of presence points (Koper and Manseau 2010, Barbet-Massin et al. 2012).

In this study, a background to presence ratio of approximately 5:1 was used to adequately define the environmental domain. Presence records were rarefied by initially removing duplicate points in ArcGIS. Then, the "Remove Duplicate Presence Records" was selected in Maxent, eliminating presence points within the same cell and reducing the impact of unequal survey methods (as suggested in Barbet-Massin et al. 2012). The total number of burrows used in this analysis was 4,548 and the total number of background points was set to 21,000.

The maximum entropy algorithm attempts to estimate a uniform distribution probability of presence data in relation to background locations constrained by values within the model variables (Baldwin 2009). However, this approach is only an estimate and does not necessarily find the only, or true, solution. As a result, it is necessary to evaluate these estimates across several replicates to find the closest to true estimate. Additionally, because Maxent is a deterministic modeling process, there must be a sufficient number of iterations to allow the model to successfully converge towards a solution. For this analysis, setting the number of replicates to use in the modeling process was done using 25, 50, and 100 replicates. The default maximum iteration number is set at 500, but due to the considerable size of data and complex feature classes used, this was set to 5,000 iterations in all model runs.

Initially, it was necessary to run a large number of models with various combinations of covariates. In this initial step, 25 replicates were used. To determine which variables collectively produce the best models, both univariate and multivariate models were assessed (Figure 29). Multivariate models were developed using a global model and a manual step-down approach, where variables were removed based on percent contribution and changes in AUC score. Once candidate covariates were identified, then the maximum number of replicates was increased to 50 iterations, and variables were removed based on an improved AUC score and low percent contribution until a group of equally likely models remained. For the remaining models, the maximum numbers of replicates were increased to 100 to ensure there were no additional changes in the AUC score.

The Maxent program offers three options for evaluating the predictive strength of the model including subsetting, bootstrapping, and k-fold cross-validation. K-fold cross-validation has been well documented in the literature as a powerful way to assess the predictive performance of a model (Merow, Smith, and Silander 2013). K-fold cross-validation subsets the data into replicates (folds) and each replicate is iteratively used as test data. The first k-1 folds are used to train the model and the k^{th} fold is used to test the model. For this analysis, k-fold cross-validation was used to test the predictive strength of each model.

The model ranking was completed by selecting models with the highest AUC and those that remained stable while increasing the regularization multiplier (Merow, Smith, and Silander 2013). The AUC metric has been heavily scrutinized because it measures how well the model can differentiate between presence and background points, which is not useful because the background points may be (unknown) presences or absences. However, this method was appropriate for this analysis because the AUC metric is a rank-based approach. By using the same data, models are directly comparable, which was the case for this analysis. When the AUC was similar between models, the models were tuned using the regularization multiplier to penalize models for being overly complex, limiting overfitting potential (Merow, Smith, and Silander 2013, Radosavljevic and Anderson 2014). The use of the regularization multiplier to differentiate between models was conducted by increasing the regularization multiplier values sequentially and evaluating model performance. If the model was overfit, AUC scores for the overfit model would notably drop below the simpler model. The general model evaluation process is presented in Figure 29.

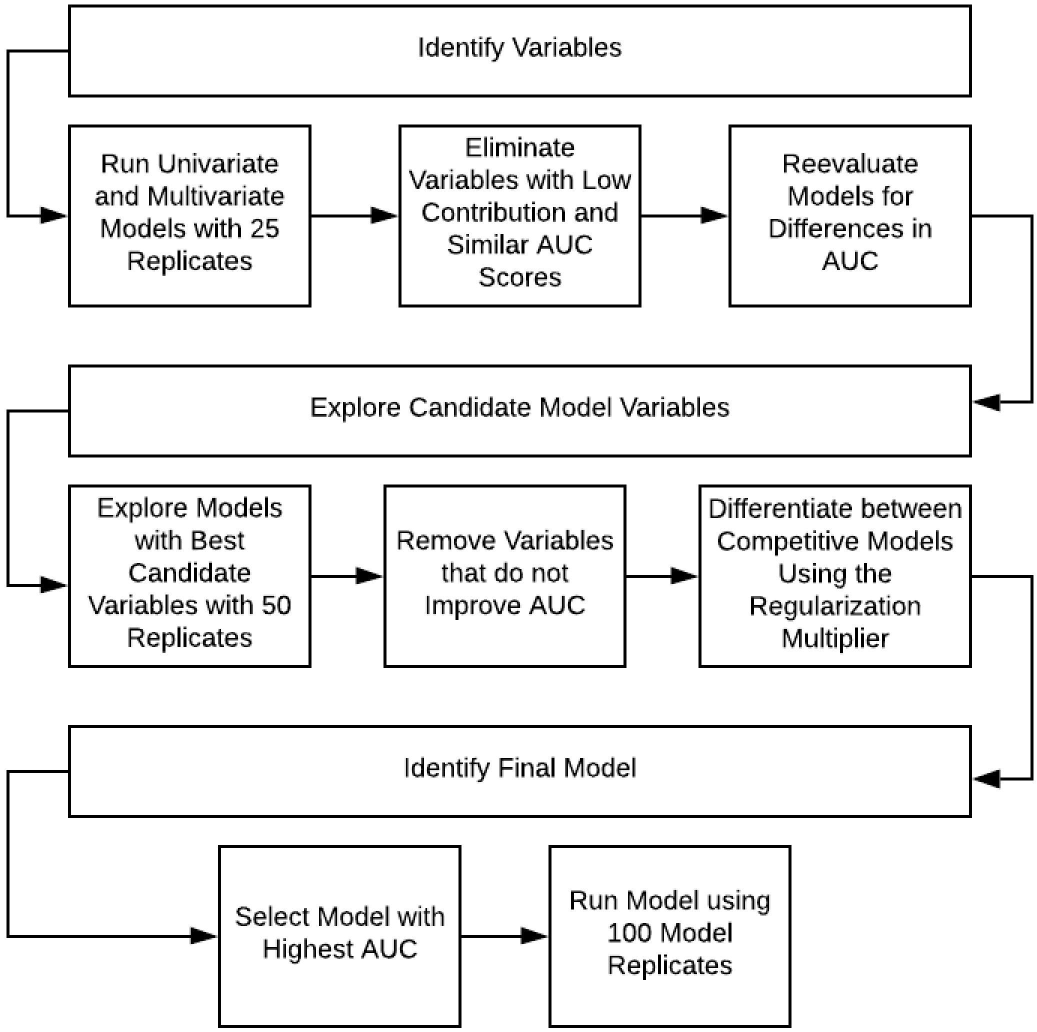


Figure 29 - General workflow for selecting variables, choosing between models, and identifying a final model.

One option the Maxent program allows is the use of a bias file to inform the model process where presence surveys have been conducted, thus limiting the influence of non-surveyed areas on model fitting. A bias file was generated for this analysis using a kernel density estimate for presence points. The file was converted to a binary format to indicate surveyed and unsurveyed areas. In initial tests, the visual outputs and low differences in AUC scores with and without the bias file suggested the bias file was overfitting the model. Thus, it was not used in this analysis.

3.2.4.1. Model Output Interpretation

Maxent produces a number of useful graphs, tables, and visual outputs for assessing model performance and relative variable importance, ranges, and contributions. These resources include AUC and receiver operating characteristics (curves, relative probability maps, variable response curves, a percent contribution table, and jackknife graphs) (Phillips, Anderson, and Schapire 2006). For this analysis, the AUC score and relative probability maps were used to evaluate the model's ability to distinguish presence locations from background points to visually inspect model results. Response curves, percent contribution values, and permutation importance values were used to evaluate the functional range of each variable and assess variable importance. Finally, jackknife graphs for each variable showed how the model performed with only that variable and without it. Model results were evaluated using these metrics to assess model performance, discriminate between variables, and inspect for signs of overfitting.

3.3. Results

Even though all variables except for vegetation were suitable for analysis, additional *a priori* elimination was conducted to narrow down the variable sets to only include those variables that would be most likely to influence ground squirrel distribution. During this process, the variable elevation was eliminated. In general, ground squirrel distribution ranges from sea level to approximately 2,200m in elevation. The maximum elevation in the study area is 650m which is well within the range of the species. As a result, this variable was eliminated out of concern that it would overinfluence the model. Additionally, if ground squirrel burrows are to occur on the lower portion of the slope, then SPI was anticipated to represent that relationship. The variables used in the final modeling included Aspect, Slope, SPI, Early Season NDVI, Late Season NDVI, and Soil Type.

3.3.1. Model Selection Results

Model results showed low to moderate ability to discern relative ground squirrel distribution at the Altamont with AUC values ranging from 0.59 to 0.768. As shown in Table 3, all univariate models had AUC scores less than a 0.7 meaning they had poor predictive strength (as established in Baldwin 2009).

Table 3 - Results of the univariate modeling process.

Variable	AUC
Slope Position Index (spi)	0.664
Late Season NDVI (lndvi)	0.657
Early Season NDVI (endvi)	0.65
Slope (slp)	0.644
Soil Type (soil type)	0.624
Aspect (asp)	0.59

The most complex model included aspect, slope, SPI, early season NDVI, late-season NDVI, and Soil Type, and had the highest AUC of 0.768. However, models that excluded slope and aspect had similar AUC values to models where those variables were included (Table 4). Additionally, the percent contribution and permutation importance of the slope and aspect variables were low (< 5 percent), indicating that the variables did not actually improve model fit. If anything, the slope and aspect variables overfit the model because each variable included will result in some increase to the AUC value. For these reasons, these variables were excluded from further analysis.

Table 4 - AUC values for models without the slope and aspect variables.

Model	AUC
endvi/lndvi/spi/slp/soil type/asp	0.768
endvi/lndvi/spi/slp/soil type	0.766
endvi/lndvi/spi/soil type	0.764

The variables early season NDVI, late-season NDVI, SPI, and Soil Type were used for candidate model evaluation. The best performing model included all four variables (Table 5). The next best model included early season NDVI, late-season NDVI, and Soil Type with an AUC score of 0.758. Based on regularization multiplier tests on the top model, the model retained an AUC score of 0.763 with a multiplier of two and the value equaled the second top models AUC of 0.758 at a value of four. Even though through the regularization process the top model equaled the second-best model, the top model AUC score did not vary drastically and the AUC score did not drop below the second-best model AUC score, thus the simpler model was not selected. As none of the models continued to improve AUC score, the model containing the variables early season NDVI, late-season NDVI, SPI, and Soil Type was identified as the final model.

Table 5 - Models developed using the top performing variables. These results were from the most competitive models based on AUC score.

Model	AUC
endvi/lndvi/spi/soil type	0.764
endvi/lndvi/soil type	0.758
endvi/lndvi	0.734
endvi/lndvi/spi	0.746
lndvi/soil type/spi	0.726
endvi/spi/soil type	0.717

3.3.2. Final Model Results

The final model was run with 100 replicates and had an AUC of 0.782 and standard error of 0.022. Variable importance was assessed by using percent contribution, permutation importance, response curves, and jackknife tests. Table 6 illustrates that the variable which contributed most to the final model was SPI (36.4 percent), followed by late-season NDVI (25.2 percent), early season NDVI (21.6 percent), and soil type (16.8 percent). However, early season and late season NDVI had the highest permutation importance indicating these variables were the most influential across replicates to predict the relative probability of ground squirrel occurrence.

Table 6 - Variable contribution and importance for final Maxent model. Variables are ranked in order of percent contribution.

Variable*	Percent Contribution	Permutation Importance
Slope Position Index	36.4	10.5
Late Season NDVI	25.2	39.5
Early Season NDVI	21.6	37.7
Soil Type	16.8	12.3

*Variable and abbreviations used within the modeling process.

Evaluation of the response curves indicated that lower slope positions, specifically the Valley category, resulted in a higher relative probability of ground squirrel occurrence, although other slope positions, with the exception of Flat, all increased the relative probability of ground squirrel occurrence (Figure 30). Late season NDVI values from approximately -0.27 to 0.1 improved relative probability of occurrence, but at the more negative NDVI values, there was higher variance, decreasing as values approached zero (Figure 30). When evaluating the individual response curves in Figure 31, late-season NDVI improved model predictive strength when approaching zero, but reducing predictive strength above 0 up to 0.1. Positive early season NDVI values were associated with higher probability of occurrence, with higher NDVI values predicting better (Figure 30). Fine (4), loamy (7), and fine-loamy (5) soil textures improved the relative probability of ground squirrel occurrence, but the fine-loamy soil texture did not necessarily result in higher probabilities in all model replicates (Figure 31). Additionally, clayey (2), coarse-loamy (3), fine silty (6), loamy-skeletal (8), very fine (10), water (1), and other (9) soil textures did not increase the probability of occurrence. Jackknife tests for each variable indicated that no model combination excluding any variable out-performed the full model (Figure 32).

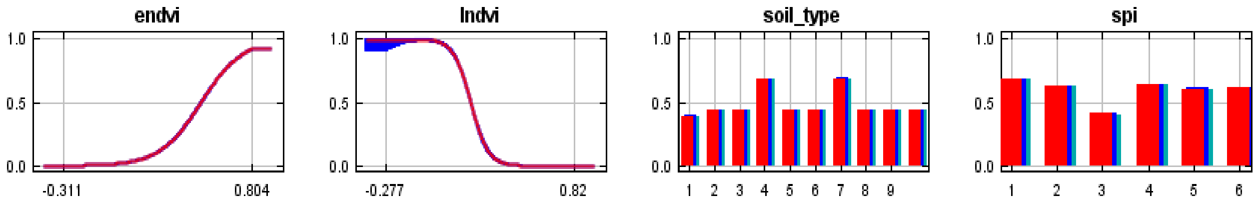


Figure 30 - These graphs display the marginal response curves for each variable within the final Maxent model. Each graph shows how the variable of interest influenced the model's predictive ability. The x-axis represents the variable range and the y-axis represents the relative probability of occurrence. Refer to Appendix A for a larger version of this figure.

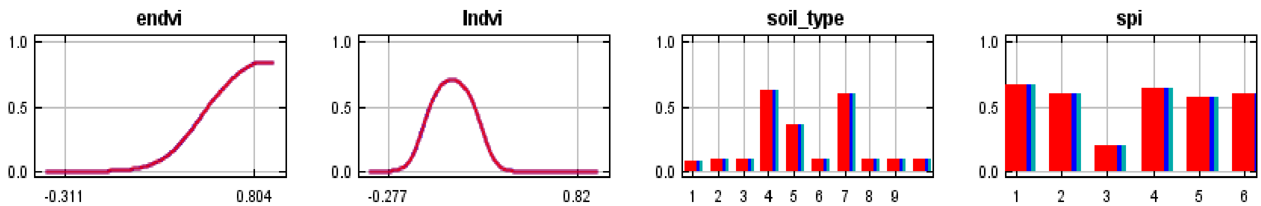


Figure 31 - These graphs show the response curves from separate univariate models. These models were from the same model run as above but they are intended to show how variable response may have differed across model replicates. The x-axis represents the variable range and the y-axis represents the relative probability of occurrence. Refer to Appendix A for a larger version of this figure.

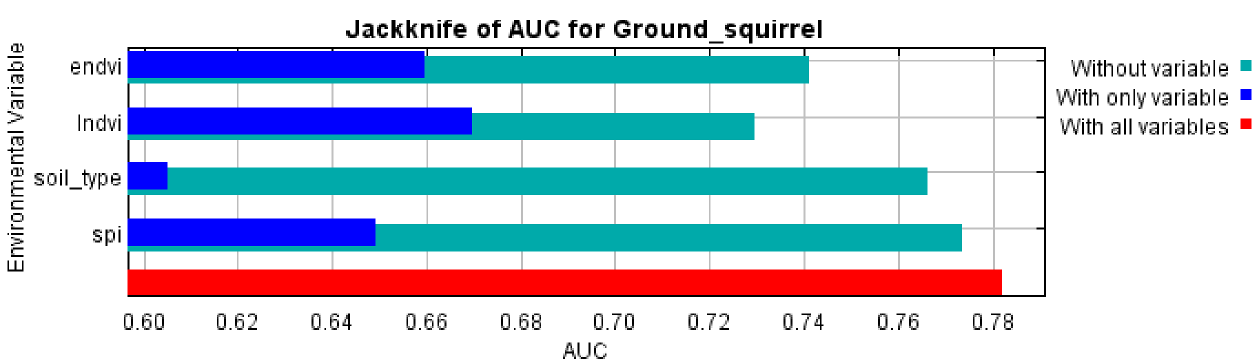


Figure 32 - Jackknife test for AUC score. The graphs show how the model AUC was impacted by using only, and leaving out, each predictor variable.

The final model output ASCII file was exported into ArcGIS Pro 2.2 for visual analysis of the results (Figure 33). Based on the final model output, most of the higher probability of occurrence locations occurred in the eastern portion of the study area. Figure 34 shows a close up of this region. It can be seen that typically, higher relative probabilities occurred within the mid-elevation drainage bottoms and lower relative probability of occurrence locations were commonly associated with roads, open water, higher elevations with high tree components, and expansive flat areas similar to agricultural fields. Based on visual inspection of the final model, it was concluded that there were no areas that had unexpected results.

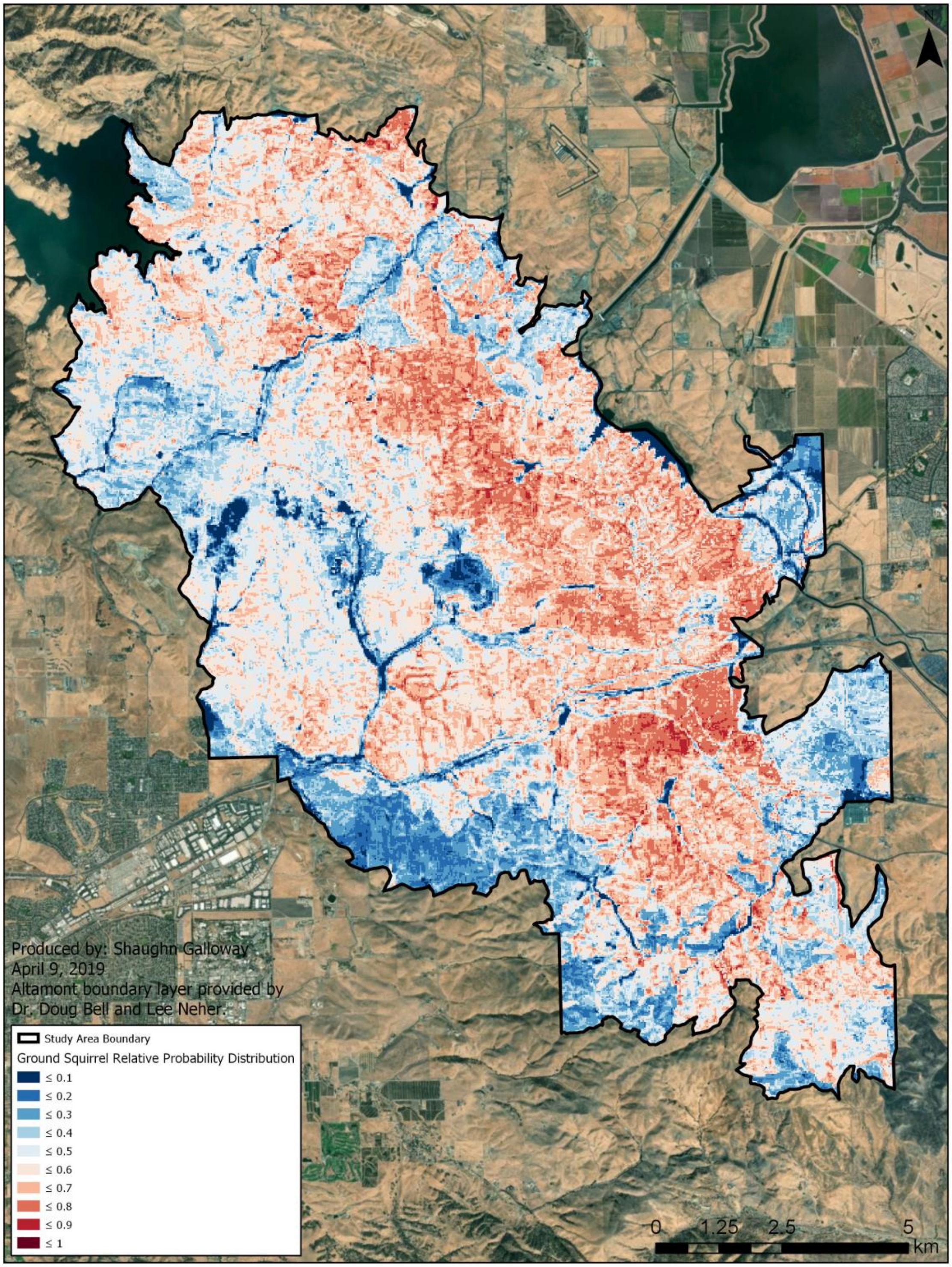


Figure 33 – Average relative probability of ground squirrel occurrence at the Altamont.

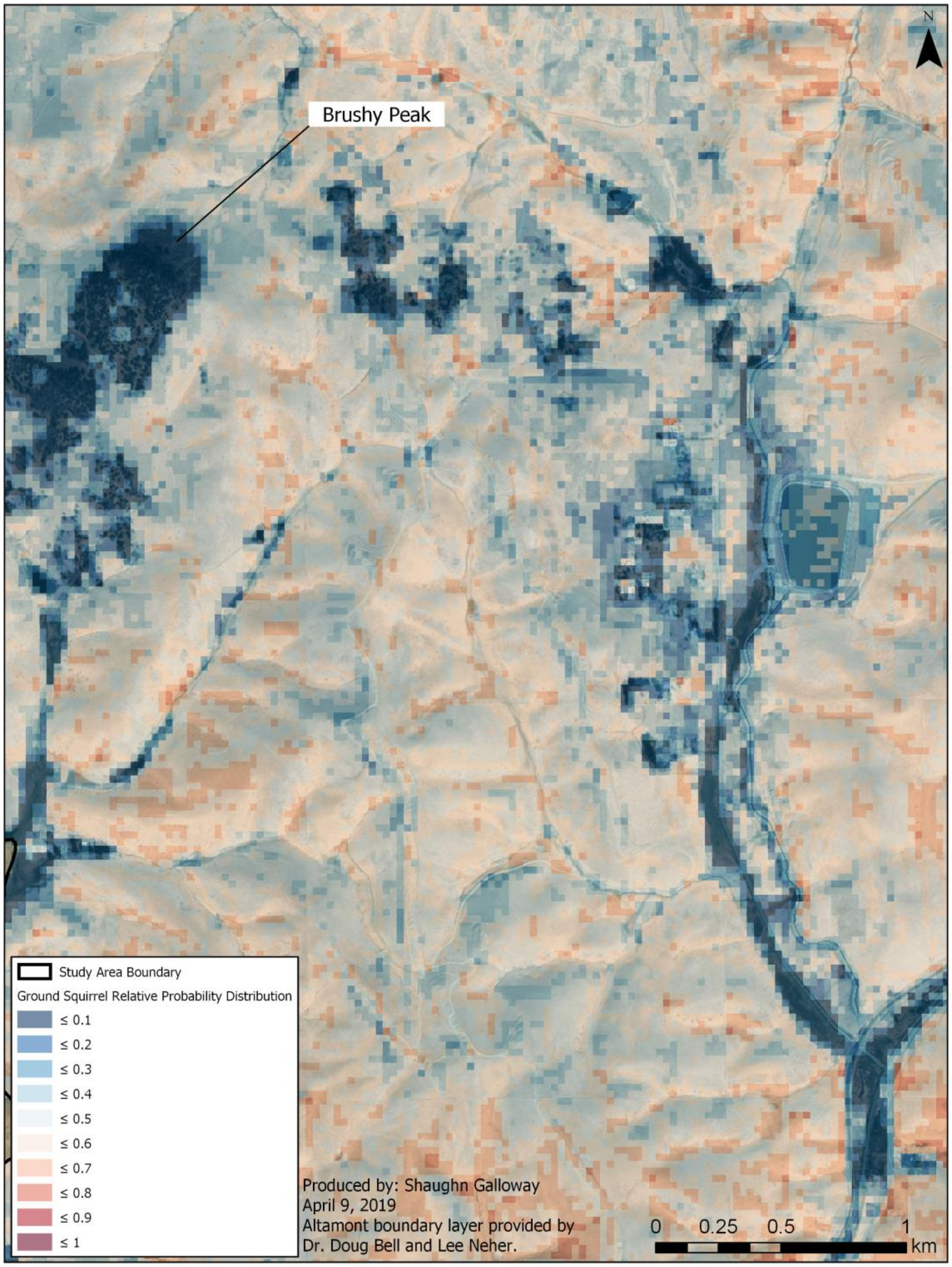


Figure 34 - Ground squirrel relative probability map. This map is intended to show the fine scale relative probability of distribution of ground squirrels.

3.4. Discussion

The variables included in the final model were consistent with what was described in the literature for supporting both the species' and burrow structures. Additionally, the AUC of the final model, as described in Section 3.3.2, is adequate for distinguishing between presence and background points (AUC = 0.782), however higher AUC values are always preferred. The values within the response curves for each variable were largely in the expected range of the system being modeled. After examining the relative prediction maps from the final model, the high relative probability of occurrence for ground squirrels was relatively evenly distributed across the study area (Figure 33). Ground squirrel relative probability of occurrence is higher in locations where the set of favorable variable values occurs (e.g. drainage bottoms) and it is less in locations were the species is less expected (e.g. areas with high levels of disturbance).

The locations with higher relative probabilities of occurrence, especially in the case of vegetation health and lower slope positions were consistent with other studies at the Altamont (Smallwood et al. 2009). The NDVI variables had the strongest influence on predicting the relative probability of ground squirrel occurrence as demonstrated by the permutation importance. The relationship with early season NDVI, where the relative probability of ground squirrel occurrence improved with higher NDVI values, was expected based on the literature. In Smallwood et al. (2009), ground squirrel burrows were found to be associated with distinctly healthy patches of vegetation, and the model results support this relationship.

The range of values associated with late season NDVI were slightly unexpected considering that negative vegetation health values improved the predictive strength of the model (e.g. response curve at or near one). However, based on the univariate response curves in Figure 31, the response curve behavior was more expected. What marginal response curves are likely showing is that model predictions improved in proportion to any live vegetation that occurred within the study area, but within the study area, these values were not common as most of the vegetation was dead so the functional range was closer to zero.

The SPI category Valleys had the highest contribution to the final model result predicting the relative probability of ground squirrel occurrence. Other slope positions also increased the probability of ground squirrel occurrence with the exception of the category Flat. This result was expected as there is nothing about slope position, other than increased predation risk, that would inhibit ground squirrel presence. This is supported by the findings of Smallwood et al. (2009), where more ground squirrel colonies occurred more frequently in lower slope positions and single burrows occurred at higher elevations. After considering the potential abundance of ground squirrels at the Altamont described within the literature, individuals may be forced to occupy less desirable higher slope positions. The colonies of ground squirrel are likely made up of multiple generations and are the well-established territories whereas the single burrows may be the result of dispersing individuals or younger individuals occupying lower quality territories.

Additionally, the predictive strength of the model improved with soil textures capable of supporting ground squirrel burrows. Based on these results, it appears the ground squirrel SDM model included biologically meaningful covariates that explain ground squirrel distribution within the Altamont.

3.4.1. Appropriateness of Model Results for Other Analyses

The primary goal of this model was to have a robust relative probability of occurrence surface capable of being used to determine if ground squirrel distribution effects non-adult golden eagle resource selection within the study area. After evaluating all the model performance metrics, it was determined that the model results were reliable to determine where the highest probability of occurrence occurs within the Altamont. The AUC score of 0.782 indicated that the model is good at discerning presence locations from background locations and results from model tuning indicated it is robust. Inspection of the variable ranges determined that they would be expected within the study area. Finally, visual inspection of the model output appears to match findings from other studies and support the variable ranges where ground squirrels may be more likely to occur. Therefore, it was concluded that the results of this model are adequate to use for the development of the non-adult golden eagle resource selection function model discussed next in Chapter 4.

Chapter 4 Golden Eagle Resource Selection Modeling

Resource selection functions are powerful statistical tools to understand how species perceive and use their environments. To accurately model resource selection, it is for the modeler to understand the life history of the species and how various resources meet those needs. The following chapter describes the development of resource selection models for non-adult golden eagles at the Altamont. This chapter is structured to provide a general background on resource requirements for golden eagles, evaluate how environmental variables relate to habitat selection, model specification, and model validation techniques, and discuss model results and implications. The goal of this model is to determine if ground squirrel distribution affects non-adult golden eagle resource selection at the Altamont.

4.1. Background: Golden Eagles

Golden eagles are a long-lived predatory species of raptor that occupy a diverse range of environments throughout the world (Figure 35) (Hunt 2002, BirdLife International 2016). Because of the wide range of environments that golden eagles occupy, it is not feasible to provide the complete background of the species. This review focuses on providing information relevant to this analysis. The following sections provide information regarding morphology, life stages, habitat requirements in the western United States, and prey preferences. Additionally, information is provided on how these life history needs relate to individuals occupying the Altamont.

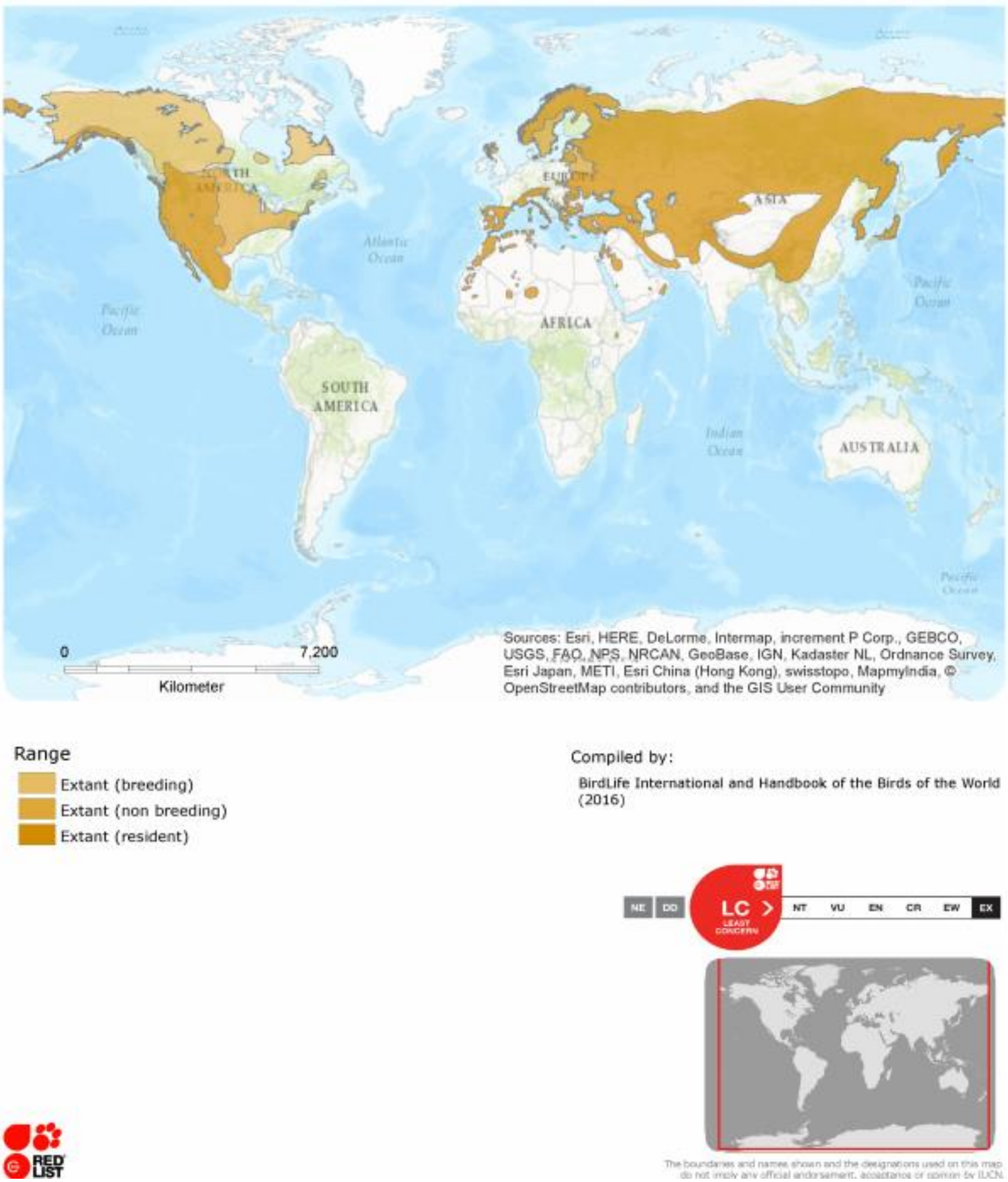


Figure 35 – Golden eagle range distribution created by IUCN. Source: BirdLife International (2016).

4.1.1. Golden Eagle Life History

Golden eagles are one of the largest species of raptor in the world with an average wingspan of two meters and weighing approximately seven kilograms (Hunt et al. 1999, BirdLife International 2016). Due to the large size of golden eagles, and high wing loading ratio, they typically select for habitats with optimal updraft to reduce the energetic costs of powered flight (Lish et al. 2016). Golden eagles have a variety of plumage patterns which vary by age class (Watson 2010). Young birds have intermixed white and brown feathers and as they get older, they progressively lose the white feathers (Figure 36). Adult golden eagles are typically brown with lighter (golden) feathers on the back of the head and wing coverts.

Figure 36 – Golden eagles in different life stages. Left: Adult golden eagle. Middle: Subadult golden eagle. Right: Juvenile golden eagle. Photo credit: Andrew Burmester.

Rugged terrain is a critical element of golden eagle territories because it provides suitable nesting habitat (e.g. cliffs) and optimal updraft for flight and forays (Watson, Duff, and Davies 2014, Marzluff et al. 1997, LeBeau et al. 2015, Hunt et al. 1999). Golden eagles in the western United States occupy a wide variety of ecosystems including forest, grasslands, agriculture, desert, and sagebrush habitats. However, areas with dense urbanization and high disturbance levels are typically avoided (Hunt 2002, Tracey et al. 2018, Tikkanen et al. 2018, Tack and Fedy 2015, Singh et al. 2016). Nesting and roosting structures include several natural and manmade features such as cliff faces, trees, and other structures (e.g. rock piles) (Crandall, Craighead, and Bedrosian 2016). Golden eagles take several years to reach reproductive maturity and have a relatively low reproductive output; only producing one to three young per year (Kuvlesky et al. 2007, Drewitt and Langston 2006, Marques et al. 2014).

Golden eagles are a long-lived species, living up to 30 years in the wild (Singh et al. 2016). The life cycle consists of roughly six stages which include juveniles (including fledglings), 1st to 4th-year subadults, and adults (Hunt et al. 1999, Hunt 2002). While subadults can and do breed, it is more common for individuals in these age classes to be members of the "floating" population (Figure 37). The floating population consists of non-paired individuals that move around the landscape searching for an open territory but do not necessarily have a territory of their own.

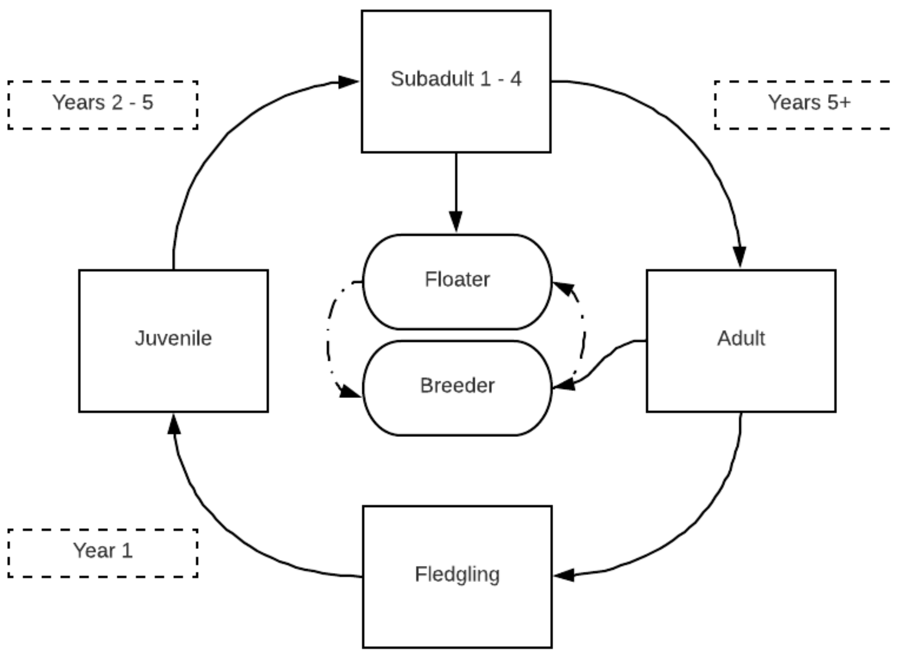


Figure 37 – The golden eagle life cycle. Diagram concept from Hunt (2002).

The diet breadth of golden eagles varies depending on regions and seasons. Based on dietary analyses of golden eagles in the western United States, diets primarily consist of jackrabbits (*Lepus ssp.*), cotton-tails (*Sylvilagus ssp.*), marmot (*Marmota ssp.*), grouse

(*Tetraoninae ssp.*), ground squirrels (*Sciuridae spp.*), fawns in the spring, and during the winter months, carrion (Watson 2010, Watson, Duff, and Davies 2014, Hunt 2002, LeBeau et al. 2015). The percentage of golden eagle diets consisting of live prey and carrion is thought to vary by age class because adults are assumed to be more adept at hunting and have higher live prey consumptions, and non-adults may depend on sources of carrion until hunting can be mastered (Watson et al. 2018). Typically, golden eagles will select for habitats where cliff faces, optimal terrain ruggedness, updraft potential, and high prey availability exist to maximize fitness (Tack and Fedy 2015, Watson 2010, Watson, Duff, and Davies 2014).

4.1.2. Golden Eagles at the Altamont Pass Wind Resource Area

Golden eagles have been extensively studied at the Altamont. Studies have evaluated large scale demographic, behavioral, and fatality trends over the history of the wind resource area (Hunt 2002, Smallwood et al. 2009, Kolar and Wiens 2017, Wiens et al. 2018, Watson et al. 2018). Several physical and environmental characteristics of the Altamont predispose this area to frequent use by golden eagles (e.g. high average wind speed, prey density, topographic features). This has also led to a high fatality rate due to collision or electrocution from site infrastructure. The collision rates between age classes impact non-adults and floaters more, as territorial adults will likely have smaller ranges and have lower exposure to turbines.

Studies at the Altamont have identified key landscape characteristics that influence site use such as rugged terrain, high wind speeds, higher elevations, preferred aspects, slope angles, vegetation types, and prey distribution. Although, golden eagle use is not likely influenced by any single environmental attribute (Smallwood and Karas 2009, Smallwood et al. 2009, Hunt 2002, Wiens et al. 2018). Behavioral analyses found that golden eagles spend a disproportionate amount of time flying when winds were coming from the southwest and easterly directions and were active at several wind speeds (Smallwood and Thelander 2005, Smallwood et al. 2009). In addition to aspect and wind speed, Smallwood et al. (2009) found eagles selected for expansive slopes and higher slope positions (e.g. upper slopes and ridges), but would occasionally use valleys. Due to the increased development surrounding the Altamont, the farms and ranches within this area provide refuge to golden eagles (Hunt and Hunt 2006). Vegetative communities within this area are dominated by open grasslands and to a lesser extent, oak woodland and shrub habitats (Hunt 2002, Wiens et al. 2018).

Primary prey species at the Altamont are different than the rest of the western United States. Results from dietary and behavioral analyses at the Altamont have indicated that ground squirrels are the primary prey source for golden eagles (Hunt 2002, Smallwood et al. 2009, Hunt and Watson 2016). California ground squirrels at the Altamont do not hibernate, which means this food source is available to golden eagles year-round. Evaluation of golden eagle flight time and prey activity has been found to be positively correlated to times when ground squirrels were above ground (Smallwood and Thelander 2005). At the Altamont, golden eagles have been found to conceal themselves behind ridges or use contour flight behaviors to ambush ground squirrels (Smallwood et al. 2009).

Several studies have documented the importance of ground squirrels to golden eagles foraging in the Altamont (Hunt 2002, Smallwood et al. 2009, Hoover 2002). However, past studies evaluating the influence of ground squirrel have done so via behavioral studies (Smallwood et al. 2009), or by using rough abundance measures of ground squirrel in areas where the researchers had access (Hoover 2002). As a result, these studies were limited to smaller portions of the Altamont. The goal of this study is to evaluate how ground squirrel distribution affects non-adult golden eagle resource selection using a relative probability of occurrence surface for ground squirrels for the entire wind resource area.

4.2. Methods

The following sections outline the methodology used to evaluate this relationship including data acquisition, variable selection and manipulation, and describe the modeling environment and the methods used to validate model results.

4.2.1. Golden Eagle Data Collection

To assess movement patterns of golden eagles in the Diablo Mountain Range, golden eagles were captured and fitted with Cellular Tracking Technologies LLC GPS/Global System for Mobil Communications telemetry units by Dr. Doug Bell starting December 18, 2012 (Bell 2017, Smallwood, Neher, and Bell 2017). Figure 38 is a copy of a graphic showing the time periods of transmission for each of the birds in their study. While difficult to read, it is included here to highlight the nature of the collective temporal ranges of the records. A more legible larger version of this figure is included in Appendix A. At the time of capture, each individual was assigned an age class which included ages from hatch year to adult. A complete description of the transmitter specifications, methods to attach units to golden eagles, and aging golden eagles can be found in Bell (2017).

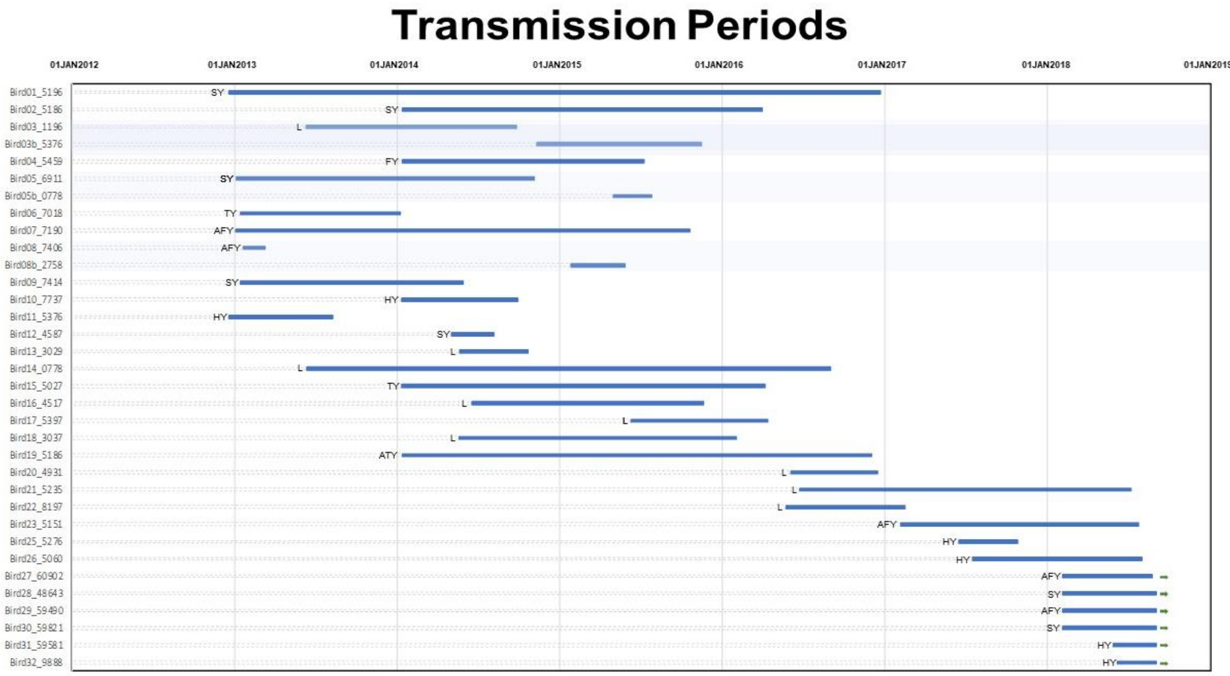


Figure 38 - Transmission period chart for all telemetered golden eagles, not all used within this study. Age classes include L= nestling, HY = hatch year, SY = second year, TY = third year, ATY = after third year, FY = fourth year, AFY = after fourth year or adult. Source: Lee Neher. For a larger version of the figure refer to Appendix A.

Telemetry units were programmed to collect a location every 15 minutes during all daylight hours and every 30 seconds three days out of the month from 2012 to 2018 (Smallwood, Neher, and Bell 2017, Bell 2017). While fix times were called 15-minutes or 30-seconds, there was a variance in timing (e.g. not always exactly 15 minutes). Data from the units were downloaded each day the transmitter was within the range of a cell tower, or stored on board the unit and downloaded at the next available window. Collected data were then downloaded from the cloud storage site by Lee Neher for post-processing (Smallwood, Neher, and Bell 2017). The 30-second points were generalized to 15-minute. Data were generalized by aggregating the 30-second data using approximately 900-second windows. These generalized points were included with the 15-minute point data.

The positional accuracy of the units was assessed by Dr. Doug Bell and Dr. Shawn Smallwood using both fixed location and movement-based methods (Smallwood, Neher, and Bell 2017). These assessments used a Trimble GPS receiver with sub-meter accuracy to compare location fixes by leaving transmitters stationary for long periods (fixed) of time, or by fitting the transmitter to a vehicle that was driven around the Altamont (movement). These data were then compared to a LiDAR-based DEM of the Altamont for final assessment. Based on these analyses, it was determined that the transmitters have a ±27m vertical and ±10m horizontal positional accuracy. Because of the varying degree of accuracy in the vertical strata, this information was not used for analysis. Additionally, the horizontal accuracy was well within the 30m resolution of the environmental data used for this analysis.

4.2.2. Telemetry Data Management for Modeling

Telemetry data for this analysis incorporated data from December 18, 2012, to December 15, 2018 (Figure 38). Because the individuals fitted with transmitters spanned multiple age classes and study years, individuals were subset into adults and non-adults. Hatch year to fourth-year subadult was used to classify non-adults and anything after was classified as an adult. Some individuals left the non-adult age class within the duration of the study. For these individuals, the data were subset based on the year they exited the non-adult age class to incorporate the transition. For this analysis, only non-adult golden eagles were used to evaluate the effect of ground squirrel distribution on resource selection.

The 15-minute telemetry data was used for this analysis because not all of the individuals had 30-second location data for the entire duration of the study (Bell 2017, Smallwood, Neher, and Bell 2017). Additionally, by not using the 30-second location data, the potential for spatial and temporal autocorrelation was reduced. To ready data for analysis, data were projected into

NAD 1983 UTM Zone 10 N and limited to "movement only" points. Maximum extent polygons were developed for each individual to constrain background points. Background points were generated and merged with used points and all point layers were attributed with values from predictor variables. The steps completed in this study are shown in Figure 39 and discussed in the following sections.

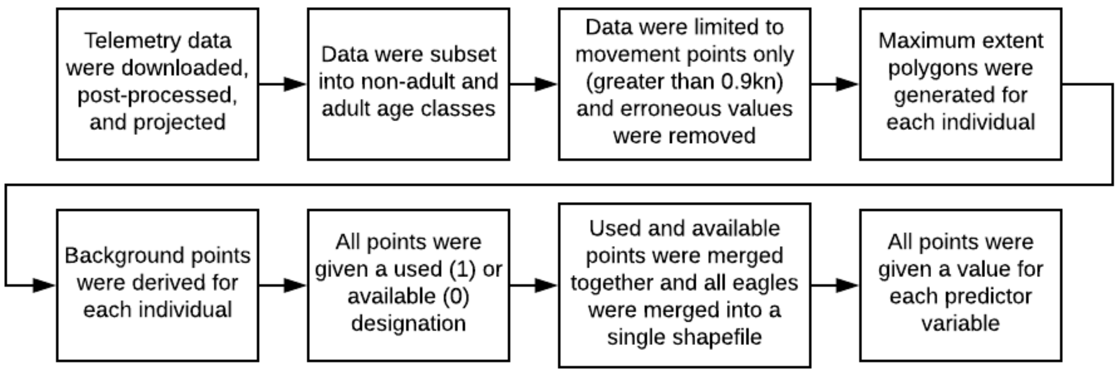


Figure 39 - Golden eagle telemetry data processing steps for use in resource selection modeling.

4.2.2.1. Rarifying Data and Validation

Once the golden eagles were classified as adult or non-adult, the data were rarefied to only include points where the individual was actively moving. This was done because rarifying data has been documented to reduce the effects of spatial and temporal autocorrelation. In addition, this step has been recommended in previous analyses due to differences in the nature of the flight and perch behaviors (LeBeau et al. 2015, Tikkanen et al. 2018). Because golden eagles can remain perched for several hours at a time, large numbers of stationary fixes can lead to clusters of spatially autocorrelated points (Figure 40). By removing perch points, the potential for temporal autocorrelation is also reduced, because within 15-minutes an individual can access any portion of the study area which reduces the effect of the previous step influencing the next step (Watson, Duff, and Davies 2014).

Figure 40 – Perched golden eagle. Photo credit: Andrew Burmester.

This study identified movement by selecting points where the accelerometer reading was ≥ 0.9kn at the time of acquisition (Tikkanen et al. 2018). This method assumed the individual was moving if the accelerometer reading was ≥ 0.9kn and for the generalized 15-minute data, the speed at the time of fix was accurately transferred to the final point. Based on discussions with Cellular Tracking Technologies LLC representatives, there was no reason to assume the accelerometers were inaccurate. Therefore, if speed was greater than 0kn, the bird was likely moving (Andrew McGann, Email to author, January 24, 2019). Additionally, during the post-processing phase, a standardized procedure was used by Lee Neher to ensure correct attribution. For these reasons, the data were suitable for the purposes of this study within the context of the aforementioned assumptions.

In addition to selecting movement only points, these locations were further evaluated based on the distance traveled. This was done to eliminate any spurious points that may not be reliable fixes. Points were evaluated by distance traveled in relation to the time interval (~15 minutes), spurious distance points were removed (e.g. traveling 150,000m in 15-minutes). As a result of the rarefication process, approximately 30 to 80 percent of the data per individual were removed and resulted in some individuals not being used in modeling due having too few points (e.g. < 100 points). The final sample size for this analysis included 14 birds and number of used points per individual ranged from 105 to 9,482 (Figure 41). Based on previous studies, this sample size should be adequate for the modeling approach used in this study (Tikkanen et al. 2018, Watson, Duff, and Davies 2014, Bolker et al. 2009).

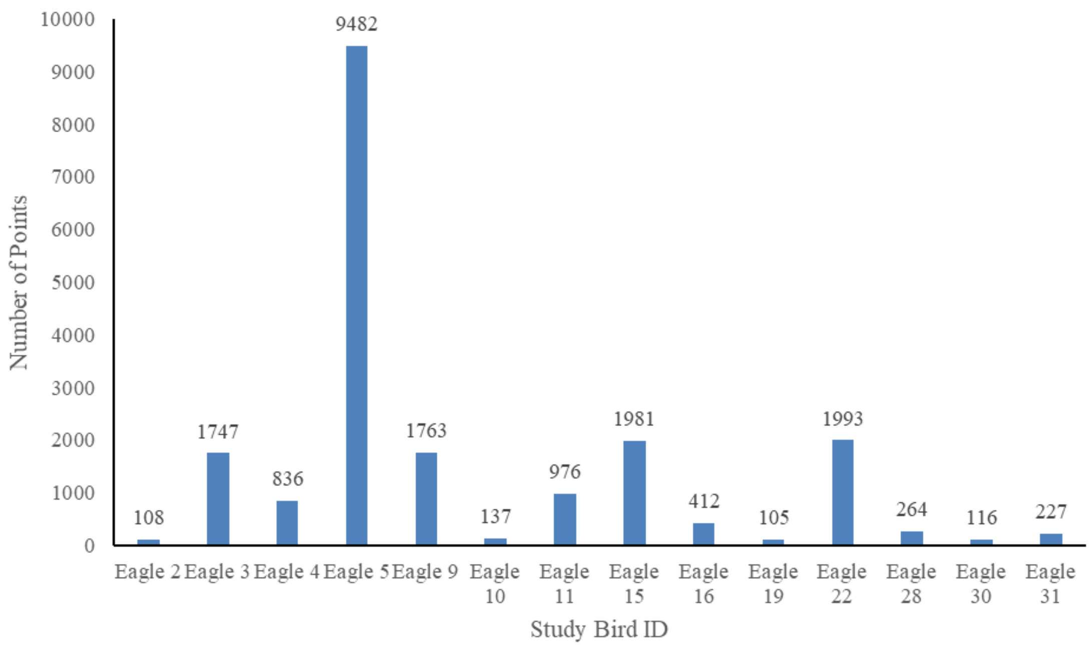


Figure 41 - Number of points by individual used within analysis following data management.

4.2.2.2. Developing Maximum Extent Polygons

When developing the background points, it was necessary to constrain the distribution to the areas where individuals had access. This step was important because not all individuals had access to all resources within the study area. If the individual did not come in contact with a resource, it could not be selected or avoided (Long 2018). For example, if one individual only used the far southern portion of the study area, they would not have access to resources in the northern portion of the study area. Thus, these results could then bias the model outcome because the individual would be reported as not selecting a particular resource when the individual never had an opportunity to come across it.

If all the telemetry data for an individual is available, then the appropriate constraining mechanism would be the home range of the individual. This would typically be delineated using either a 95 percent kernel-based utilization distribution (UD) which provides the intensity of use and maximum spatial distribution or a minimum convex polygon (MCP) (Long 2009, Marzluff et al. 2004). While the UD is the preferred method, if the volume of the UD cannot be accurately estimated then it is more appropriate to use an MCP (Long 2009). This study only had access to points within the Altamont, therefore it was impossible to calculate the true volume of a UD because home ranges exceed the boundary of the study area. For this reason, a 100 percent MCP was used to establish the area for which the individual had access. The 95 percent MCP was not selected because, during the 15-minute interval, individuals could have traveled beyond the actual fix location at the edge of the polygon. The 100 percent MCP was used to try and capture the maximum area used by an individual, thus adequately defining the available resources. For these reasons, this study uses the term "maximum extent" instead of the word home range because the MCPs are not representing the true home range.

To establish the maximum extent polygons, individual point data was transferred into R Studio version 3.4.2 (Calenge 2006, R Core Team 2017). Using the "*adehabtiatHR*" package and "*mcp*" function in R, 100 percent MCPs were delineated for each individual. The maximum extent polygons were then transferred into ArcGIS Pro 2.2 to generate background points. In ArcGIS Pro 2.2, MCPs were clipped to the study area to exclude resources that occur outside of the study area and the extent of the data (Figure 42). One caveat to the methods used to delineate the maximum extent polygons is that because this study only had access to points within the wind resource area, the importance of the study area to non-adult golden eagles in this analysis is unknown.

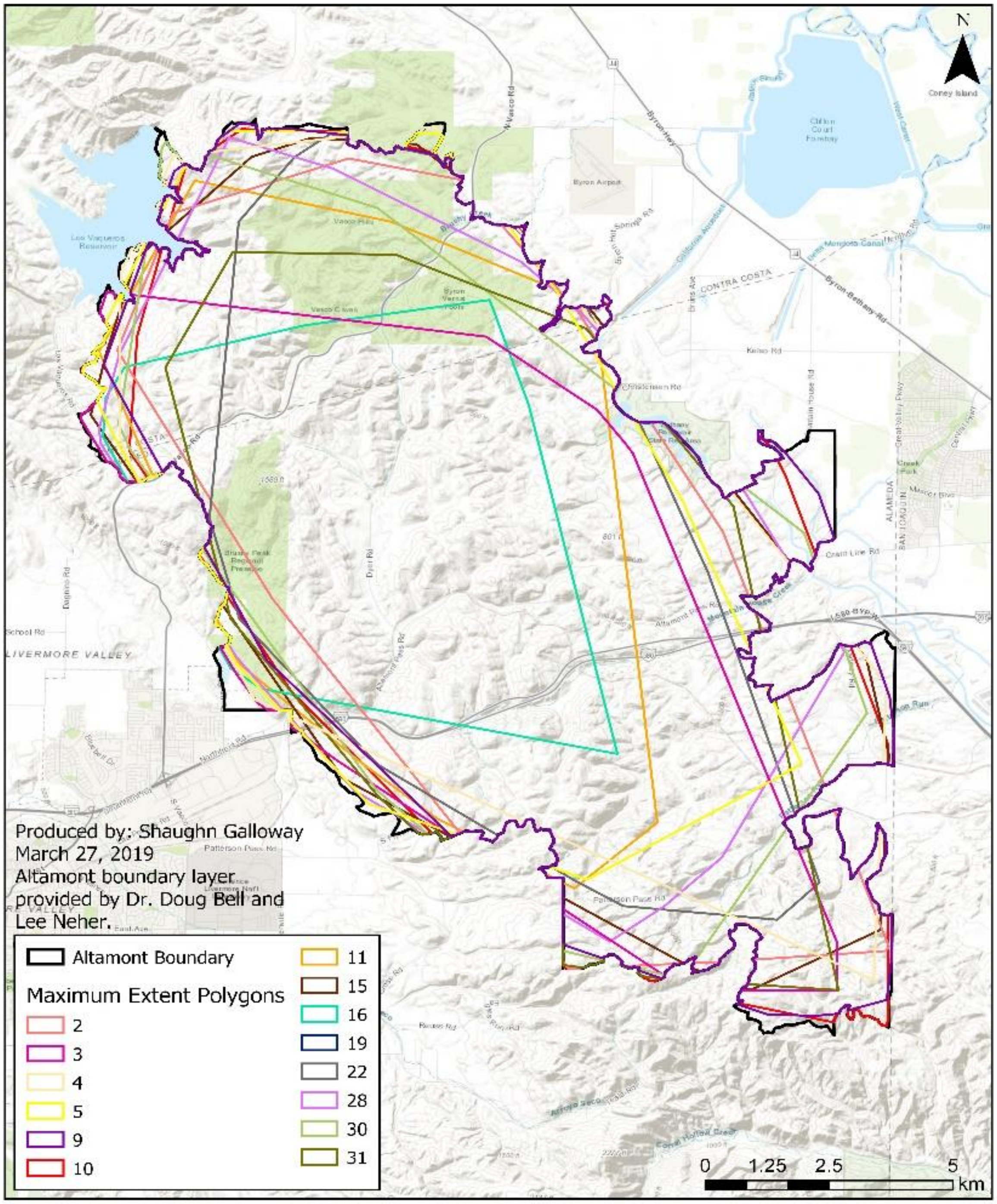


Figure 42 - Maximum extent polygons for each non-adult golden eagle. Each maximum extent polygon number corresponds to each individual ID.

For each individual, background points were created using random points in ArcGIS Pro 2.2 and were constrained to the maximum extent polygons. The logit-link function used by the GLMM assumes nearly equal presence to background points. Background points were generated at 1.5x the number of presence points (Zuur et al. 2009, Tikkanen et al. 2018). The number of background points was set to slightly more than the presence points to adequately define the environmental conditions within the study area as documented in previous studies (Tikkanen et al. 2018, Watson, Duff, and Davies 2014). All points were given an attribute field called "Used", where the value one indicated used and a value of zero indicated available. Both layers were merged together in ArcGIS Pro. All points were attributed with predictor variable values in ArcGIS Pro. Each attribute column was evaluated to ensure that there were no missing data or erroneous values.

4.2.3. Variable Selection

The scope of this analysis was to determine if ground squirrel distribution affects non-adult golden eagle resource selection at the Altamont. Variables used in this analysis were selected because they have been found to fulfill golden eagle resource requirements meeting several life history needs outlined within the above sections. The variables considered for this analysis included elevation, slope, aspect, ground squirrel distribution, vegetation type, vector ruggedness measure (VRM), and orographic lift potential (Table 7). The following sections provide additional information about each variable including; purpose, origination, and processing steps. In general, each variable was downloaded from their respective sources and projected into NAD 1983 UTM Zone 10N. All variables were converted into 30m resolution and clipped to the study area.

Table 7 - Environmental variables evaluated for non-adult golden eagle GLMM.

Variable	Data Type	Resolution	Source
Non-adult Golden Eagle Telemetry Points	Point	10m	Dr. Doug Bell and Lee Neher
Elevation	Raster	30m	USGS 3-DEP
Slope	Raster	30m	USGS 3-DEP
Eastness	Raster	30m	USGS 3-DEP
Ground Squirrel SDM	Raster	30m	Ch. 3
Vector Ruggedness Measure	Raster	30m	USGS 3-DEP, Sappington, Longshore, and Thompson (2007)
Orographic Lift	Raster	30m	USGS 3-DEP, Miller et al. (2014)
Vegetation Type	Raster	30m	USGS LANDFIRE

4.2.3.1. Elevation, Slope, and Aspect

As discussed in Section 4.1, specific elevation, slope, and aspect characteristics were all found to influence golden eagle resource selection at the Altamont (Smallwood et al. 2009). To create variables for elevation, slope, and aspect, a DEM was downloaded from the USGS's 3DEP program (U.S. Geological Survey 2017a). The selected resolution of the DEM was one arc-second, equating to approximately 27m. The DEM was then converted to 30m resolution using bilinear interpolation. The slope was calculated from the DEM to create the slope variable. Values were calculated in degrees to be consistent among other variables and processes (e.g. slope position index used in the ground squirrel distribution model in Section 3.2.2.4).

Aspect was calculated using the DEM. Because aspect ranges from 0 to 360°, with both 0° and 360° representing north, this variable required further manipulation to be used in the analysis. As discussed in Section 3.2.3.1, the majority of the ridgelines in the Altamont extend in a northwest/southeast direction, with aspects predominantly in an east/west direction. Aspect was converted to eastness, which is a continuous measure of aspect, ranging from -1 to 1. Where negative one represents west and positive one represents east. To convert the aspect layer into eastness, the aspect layer was first converted to radians and then converted to eastness using Equation 3 (Miller et al. 2014).

$$Eastness = sin(aspect) \tag{3}$$

4.2.3.2. Ground Squirrel Species Distribution Model

The ground squirrel relative probability layer developed in Chapter 3 was used to assess the potential ground squirrel distribution at the Altamont. While this model cannot inform about the abundance of prey at any given location, it does provide a metric for where prey may be more likely to occur. It is likely that foraging golden eagles use visual cues associated with ground squirrel burrows (e.g. distinct vegetation clumps) to stalk prey, increasing chances of success (Smallwood et al. 2009). This variable used the logistic output from the Maxent model to create the relative probability of ground squirrel occurrence surface. The values within this raster give the relative probability of ground squirrel occurrence from 0 to 1, with one representing the highest relative probability of occurrence.

4.2.3.3. Vector Ruggedness Measure

Based on previous research, terrain ruggedness has been identified as an important abiotic feature associated with golden eagle resource selection (Watson, Duff, and Davies 2014, LeBeau et al. 2015, Tikkanen et al. 2018). In wildlife ecology, two primary methods have been used to quantify landscape heterogeneity: terrain ruggedness index (TRI; Riley, DeGloria, and Elliot 1999) and the vector ruggedness measure (VRM; Hobson 1972) (Sappington, Longshore, and Thomson 2007). The TRI measure suggested by Riley, DeGloria, and Elliot (1999) uses a 3x3 cell moving window to evaluate terrain heterogeneity at each cell. Each neighborhood cell in the DEM is squared to create positive values and are then averaged. The terrain ruggedness index is then calculated by taking the square root of the averages and values are then binned into ruggedness categories. However, this method has been criticized for being correlated with slope (Sappington, Longshore, and Thomson 2007).

Recent studies in wildlife ecology have suggested VRM is a superior approach for calculating terrain ruggedness (Sappington, Longshore, and Thomson 2007). VRM was determined to be a more appropriate terrain ruggedness variable because of its ability to assess heterogeneity in a 3D format, providing a better overall measure of topographic heterogeneity. Vector ruggedness measure is a continuous metric, with values ranging from 0 to 1, however, values are typically less than 0.4. The toolbox created by Sappington, Longshore, and Thompson (2007) used to calculate VRM was downloaded and added into ArcGIS. There were no guidelines for developing an adequate search radius for the VRM tool, so neighborhoods were assessed ranging from 3x3 to 10x10. Figure 43 shows the results for 3x3 and 9x9 windows. After exploring several moving window neighborhoods, a 3x3 moving window appeared to best fit the landscape considering the resolution of the data in this analysis. This moving window size is also consistent with the findings of the SPI variable used in Chapter 3.

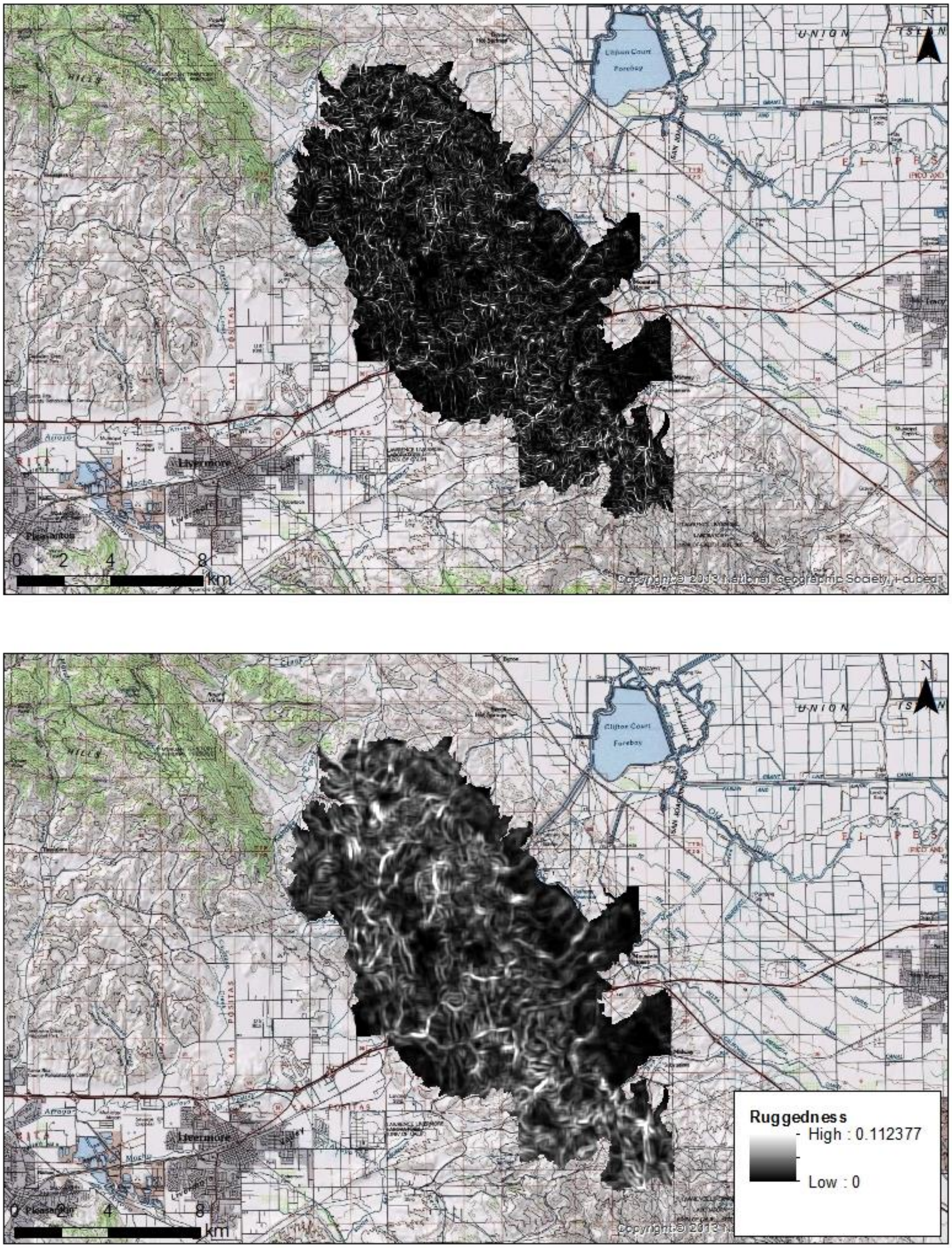


Figure 43 - Difference in terrain heterogeneity using vector ruggedness measure. The top map was created using a 3x3 cell search radius. The bottom map was created using a 9x9 search radius.

4.2.3.4. Orographic Lift Potential

Several studies evaluating eagle resource selection have highlighted the importance of not only rugged terrain, but other features associated with rugged terrain that would result in higher updraft potential (Miller et al. 2014, Watson, Duff, and Davies 2014, LeBeau et al. 2015). One of the methodologies referenced in the literature to calculate orographic lift was proposed by Brandes and Ombalski (2004) (Miller et al. 2014). This method calculates updraft potential (*w(x)*) using wind speed, wind direction, slope (in radians), and aspect (in radians) as shown in Equation 4.

$$w(x) = wind\ speed\big(sin(slope)\big) * (cos(wind\ direction * aspect)) \tag{4}$$

Orographic lift was calculated for northwest (315°) and southwest (225°) aspects representing the prevailing wind directions in the Altamont (Smallwood, Rugge, and Morrison 2009, Smallwood et al. 2009, Smallwood and Karas 2009). To assess wind speed for the study area, a layer of wind speed at 50m above ground level was downloaded from the National Renewable Energy Laboratory (NREL 2018). The resolution of this layer was 200m, so an average wind speed for the entire study area was estimated. The average wind speed used in the orographic lift equation was 7m/s. This analysis resulted in two orographic lift variables representing northwest and southwest orographic lift potential (Figure 44).

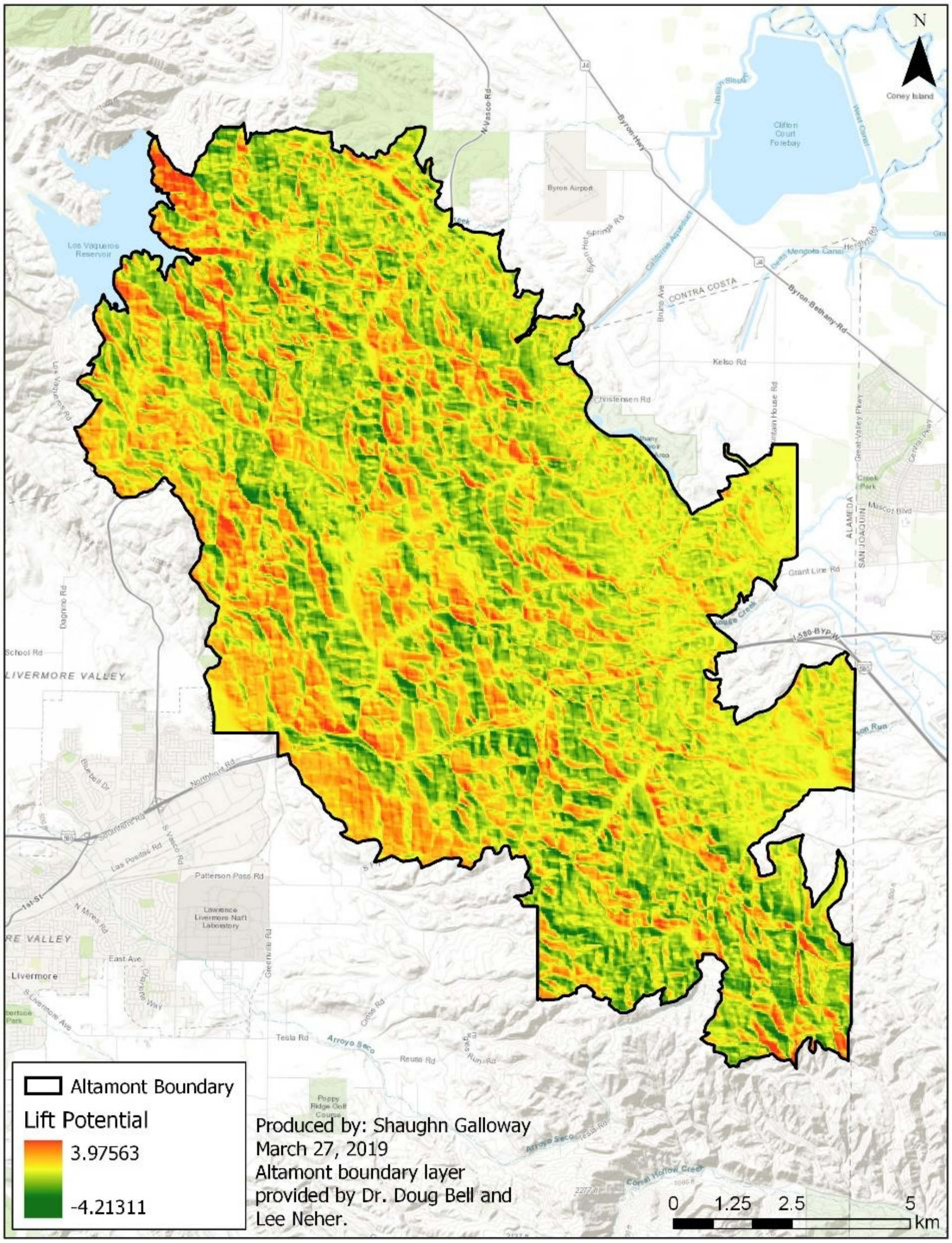


Figure 44 - Example of orographic lift from the southwest. Calculated using Equation 4.

4.2.3.5. Vegetation Type

At the Altamont, golden eagle habitat selection has been associated with different vegetation types (Wiens et al. 2018, Kolar and Wiens 2017, Hunt 2002). To get the distribution of vegetation within the study area, the Existing Vegetation Type (EVT) layer was downloaded from the USGS LANDFIRE program (U.S. Geological Survey 2017b). Vegetation classification was based on remotely sensed imagery from 2013 to 2017, with priority given to 2016 imagery. The default number of categories in EVT included 15 vegetation classifications. Because the vegetation variable is categorical, having 15 classes would have caused convergence issues with the GLMM model. Vegetation was collapsed into five categories which included classes Shrub, Herbaceous, Tree, Developed, and Water (Figure 45). These broader vegetation classes were sufficient for the purposes of this analysis (Wiens et al. 2018, LeBeau et al. 2015).

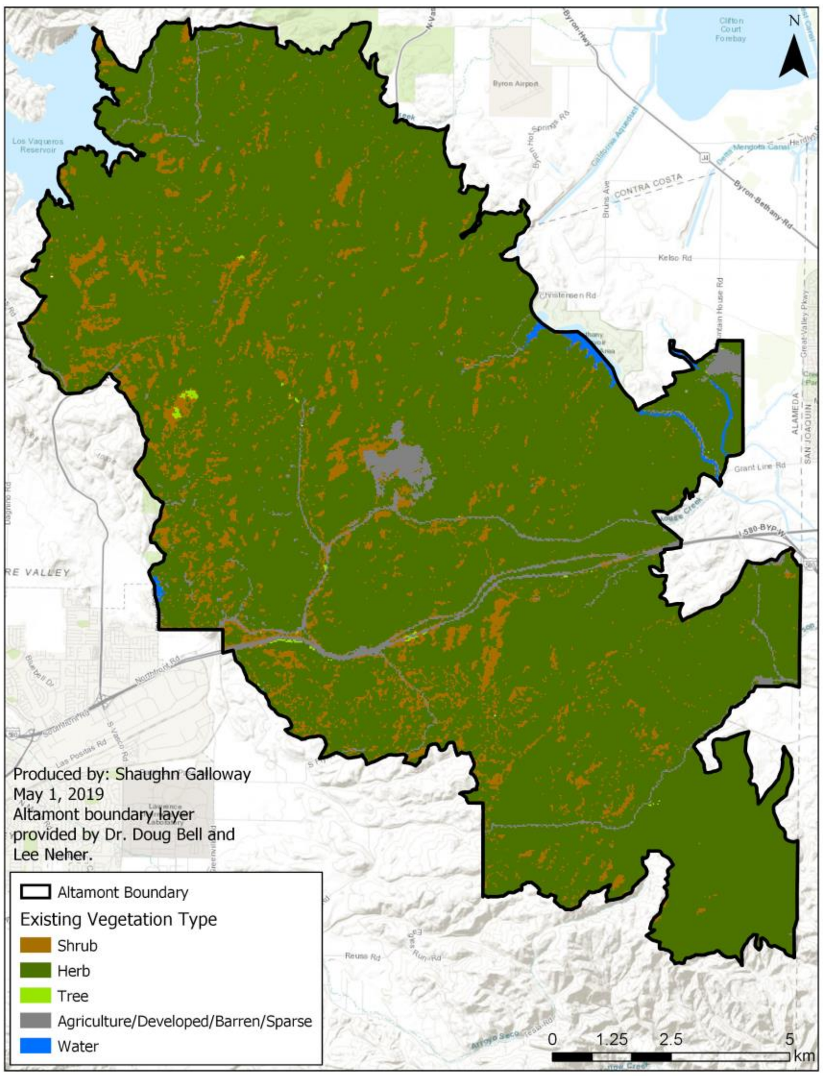


Figure 45 - Existing vegetation type within the Altamont. These classes were collapsed from the original 15 class existing vegetation class layer.

4.2.3.6. Summary and Variable Limitations

The variables described above have all been documented within the literature to affect the potential for resource use by golden eagles at the Altamont. Variables were assessed for collinearity using a Pearson's correlation coefficient. Variables were considered colinear if the coefficient was > 0.6 (R Core Team 2017). If the variables were colinear, then one of the variables was excluded from further analysis. The final variable Pearson's correlation test results are presented in Figure 46.

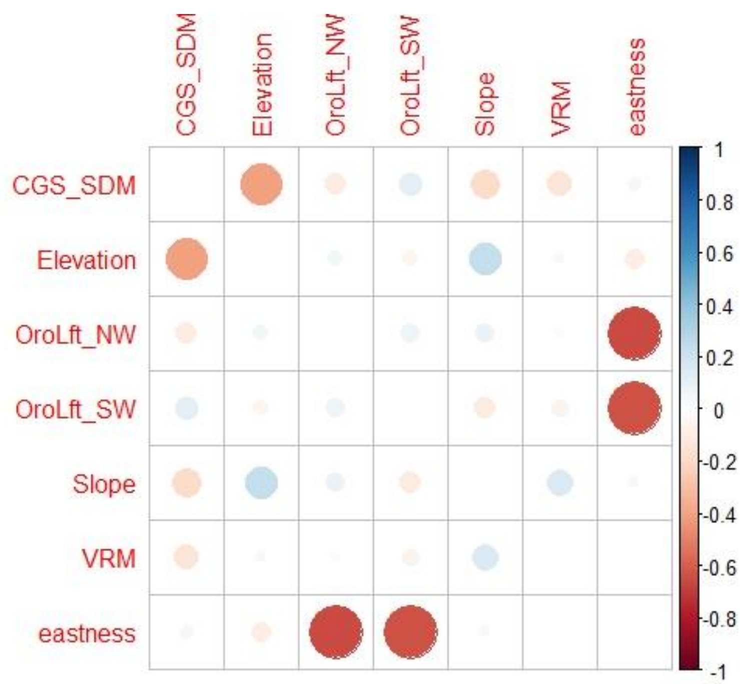


Figure 46 - Correlation matrix for Pearson's correlation coefficient scores. CGS_SDM = Ground squirrel SDM, OroLft_NW = Orographic lift from the northwest, OroLft_SW = Orographic lift from the southwest.

The results of the Pearson's correlation test indicated that both northwest and southwest orographic lift were highly correlated with eastness. Due to the high degree of correlation with eastness, both orographic lift variables were removed from the analysis. This selection was made because the orographic lift variables only encompassed two directions and eastness was able to evaluate a larger range of directions. In addition to the orographic lift variables being removed, the variable elevation was also excluded from further analysis. While golden eagle activity has been associated with higher elevation, it is not likely that elevation is a critical factor for use (e.g. elevation can be high but flat), but more so heterogeneous topography. For this reason, it was assumed that the VRM measure would likely better represent topographic features, like rugged terrain, which are more conducive to creating updraft aiding in flight. The final variables used in this analysis included slope, eastness, vegetation type, the relative probability of ground squirrel distribution, and VRM.

4.2.4. Resource Selection Analysis

As discussed in Chapter 2, there are several methods for estimating resource selection functions (RSF) (e.g. GLMM, GLM, GAM) (Zuur et al. 2009). At the scale for which the data were available, constrained to a subset of the home range, this analysis used a third order use-vs-available RSF (Johnson 1980). Based on the initial assessment of the telemetry data, there was unevenness in sample sizes and sample durations, making a standard GLM approach inappropriate (Zuur et al. 2009). Additionally, the sample of individuals collected (n=14) was not likely representative to the true population, as the sampled breeding population alone was approximately 160 individuals with an unknown floating population (Hunt 2002, Wiens et al. 2018). For these reasons, this analysis used the GLMM statistical approach because it allowed for the comparison of unequal datasets and for the incorporation of both fixed and random effects to account for individual variation (Bolker et al. 2009).

As discussed in Section 2.3.2.1, there are several assumptions associated with RSFs and GLMMs, some of which are essential to meet and others that have more flexibility (Zuur et al. 2009, Zuur, Ieno, and Elphick 2010, Long et al. 2009, Long 2018). The assumptions relevant to this study were evaluated at different points during the modeling process. During the model set up and data processing phases, sample units were evaluated for independence. To account for spatial and temporal autocorrelation, data were rarefied, a spatial autocorrelation variable was developed, and a temporal autocorrelation structure was specified in the *"glmer"* function. Resources were evaluated for consistent availability, outlined in Section 4.2.4.2. Once the best performing model was estimated, an inspection of the residuals was conducted to ensure the absence of heteroscedasticity, overdispersion, and zero inflation. The following sections outline the modeling environment used, the process used for model selection, how model assumptions were validated, and how results were interpreted.

4.2.4.1. Modeling Environment

Several packages in R have been used to estimate GLMMs. This analysis used the package *lem4* and *glmer* function to estimate non-adult golden eagle resource selection (Bates et al. 2015). To set up the GLMM, a distribution, link function, and random effects structure were selected (Bolker et al. 2009). Because the data used in this analysis represented a used (1) versus available (0) study design, a binomial error distribution was selected using a logit link function (Long et al. 2014, Bolker et al. 2009, Harrison et al. 2018). The study design used to collect the golden eagle telemetry data resulted in uneven sample periods and number of subsamples. To compensate for this, Individual ID was used as a random effect within the GLMM. A compound symmetry correlation structure was used to model the effects of temporal autocorrelation within individual points. The compound symmetry structure is the default for the *lem4* package, but generally works for most models, and assumes equal variance and covariance among temporal clusters (Ryan Long, email to the author, March 11, 2019, Long et al. 2014, Bates et al. 2015). Spatial autocorrelation was reduced through rarefication and use of an autocorrelation correction variable (Tikkanen et al. 2018). Because only one random effect was used (Individual ID), Laplace estimation was used for the calculation of parameter estimates (Bolker et al. 2009).

Because this study attempted to determine if ground squirrel distribution would affect non-adult golden eagle resource selection, resource selection was assessed using the magnitude of affect each variable had on selection. Variables were standardized using the *scale* function in *lem4* which allowed for direct comparison of parameter estimates on resource selection (Long et al. 2014, Bates et al. 2015). The only categorical variable, vegetation, was converted into a factor to inform the model of the data structure. Estimates were in relation to the reference category "Herbaceous" vegetation because it had the highest abundance within the study area (Figure 45). Once the variables were converted into factors and scaled, the global model was specified using random effects for Individual ID and included the fixed effects VRM, slope, vegetation, CGS burrow distribution, and eastness.

To establish a fixed effects structure, the global model was used as a starting point and a step-down approach, using the *drop1* function in the *Stats* package in R, was conducted to arrive at a candidate set of variables (R Core Team 2017). To distinguish between model performance, Akaike Information Criteria (AIC) was used and models within 2 ΔAIC points were considered equally likely models (Long et al. 2014, Tikkanen et al. 2018, Watson, Duff, and Davies 2014). Competitive models were evaluated based on model weight, using the *model.sel* function in the R package *MuMIn*, where the model with the most support (e.g. greater model weight) was used to incorporate individual-level random effects (Barton, 2018, Long et al. 2014).

Once the optimal fixed effects structure was identified, uncorrelated random slopes based on the grouping variable (Individual ID) were applied to variables for which there may be differences in selection within the individual level (Harrison et al. 2018). While some literature recommends applying random slopes to all variables, it is not necessarily good practice because random slopes should only be included if biologically justifiable. For this analysis, random slopes were tested for all of the continuous variables allowing different foraging capabilities, differences in wind patterns, and accommodating for differences in site topography between the northern and southern portions of the study area (e.g. if individuals only used a portion of the study area). If the individual level random slope substantially improved the model AIC score (e.g. ΔAIC = ~100) then it was incorporated, but if there were no significant improvements in AIC they were removed. The top-performing model was considered to be the model, or group of competitive models, with the lowest AIC score (Harrison et al. 2018).

Parameter estimates were evaluated on the log-odds scale, where positive values implied selection and negative values implied avoidance (Watson, Duff, and Davies 2014). The effect of variables on resource selection was determined using two criteria. First, how far negative or positive the point estimate was and second, based on the degree in which the 95 percent confidence intervals (95% CI's) did not overlap zero (Wiens et al. 2018). If the 95% CIs for a single variable overlapped zero, the variable was considered to be uninformative and 95% CIs excluding zero were considered informative (Watson, Duff, and Davies 2014, Wiens et al. 2018, Long et al. 2014).

Once the final model was identified, it was tested for its predictive capacity using leave-one-out cross-validation (LOOCV). This approach was selected over typical k-fold cross-validation because it allows for the ability to exclude an entire individuals' data for training and testing folds and is unaffected by spatial autocorrelation (Roberts et al. 2018). For the LOOCV, the data were subset by Individual ID, then models were trained and tested for each individual. The results of the LOOCV were then averaged to assess the models overall predictive performance, where values < 0.7 were considered poor, values between 0.7 to 0.9 were considered good, and anything > 0.9 was considered excellent (Roberts et al. 2018).

4.2.4.2. Meeting Model Assumptions

Because individuals were captured during different time frames (December 2012 to December 2018) and golden eagles are not considered a social species (e.g. not in flocks or herds), it was assumed that studied individuals selected for resources independently of one another. By using the compound symmetry correlation structure, the temporal autocorrelation was appropriately specified to minimize the effects of serial autocorrelation (because data are collected sequentially) which arises when using telemetry data. Spatial autocorrelation was accounted for using three steps which included data rarefication, developing a correction variable, and using LOOCV (Tikkanen et al. 2018, Roberts et al. 2017, Boyce 2006).

Using the Moran's I test in ArcGIS Pro 2.2, it was determined that there was significant spatial autocorrelation at the 1,000m scale. A correction variable was developed using the function *autocov_dist* in the *spdep* package in R, where weights were assigned to each point using inverse distance weighting considering a 1,000m search neighborhood (Bivand et al. 2012, Tikkanen et al. 2018). This correction variable was incorporated into each model to account for spatial autocorrelation by acting as a penalty variable until a top model was identified (Tikkanen et al. 2018). The model was then refitted without the correction variable and LOOCV was conducted, leaving out data for an entire individual, to determine the predictive performance of the model (Roberts et al. 2017). For these reasons it was assumed that the assumption of independence was adequately met.

The assumption of resource availability consistency over time was met for each of the variables. The majority of the variables used in this analysis were measures of topography (e.g.

ruggedness, slope, eastness). While these variables can change over long periods of time (e.g. over 100,000 years), these values remained consistent within the study period. The vegetation variable was considered to remain constant through the study period. This was assumed due to the infrequent changes in disturbance regimes and consistent management strategies (e.g. grazing) practiced by landowners within the Altamont. The ground squirrel distribution model was assumed to be consistent throughout the study period, as burrow data were collected for the range of the study period and variables used to generate the SDM were representative of the years in which the eagle telemetry study took place. For these reasons it was assumed that the resource availability assumption was met.

Following the development of the final model, the assumptions of heteroscedasticity, overdispersion, and zero inflation were evaluated using the *DHARMa* package in R (Hartig 2018). Much of the available literature suggests that these assumptions should be checked using a simulation of the model residuals (Harrison et al. 2018, Zuur and Ieno 2016). The *DHARMa* package provided an environment to simulate residuals efficiently and effectively, similar to the techniques of bootstrapping, and functions to assess overall model fit (Hartig 2018). Tests used to evaluate the model outcomes were based on the *testUniformity*, *testZeroInflation,* and *testDispersion* functions in the *DHARMa* package.

4.3. Results

Using the *glmer* function in the *lme4* package, RSFs were developed for non-adult golden eagles (Bates et al. 2015). A total of 16 multivariate models and five univariate models were assessed during the modeling process to estimate the resource selection by non-adult golden eagles at the Altamont. The following section reviews the results of this analysis, provides information on model fit and examines the predictive strength of the best performing model.

4.3.1. Model Results and Evaluation

The global model developed for the non-adult golden eagle RSF included the variables VRM, vegetation, slope, eastness, and ground squirrel distribution with a random effect for Individual ID. Two models were competitive for the fixed effects structure which included the global model and the global model without prey (Table 8). The two competitive models were evaluated using the *model.sel* function, where the model without prey had the most support with a model weight of 0.726 and was selected as the top fixed effects model (Bivand et al. 2012).

Table 8 - Modeling results to determine the fixed effects structure.
VR = Vector Ruggedness Measures, Ve = Vegetation, S = Slope, C = ground squirrel SDM, and E = Eastness.

Explanatory Variables*	AIC	ΔAIC
Vr/Ve/S/E	41787.4	0
Vr/Ve/S/E/C	41789.3	1.9
Ve/S/E	41806.0	18.6
Ve/S/E/C	41807.4	20
Vr/S/E	41856.9	69.5
Vr/S/E/C	41857.5	70.1
S/E	41873.1	85.7
Vr/Ve/E	41947.0	159.6
Vr/Ve/E/C	41948.5	161.1
Ve/E	41978.5	191.1
Vr/Ve/S	42086.9	299.5
Vr/Ve/S/C	42087.6	300.2
Ve/S	42104.9	317.5
E	42069.4	282
S	42201.6	414.2
Ve	42295.6	508.2
Vr	42409.6	622.2
C	42440.5	837.4

Using the fixed effects model, random slopes were then applied to the variables eastness, slope, and VRM. The random slope for VRM only improved model AIC by approximately ten points and was not incorporated (Table 9). Random intercepts for eastness and slope significantly improved the model AIC score and were included in the final model.

Table 9 - Results from applying individual-level random slopes.
VR = Vector Ruggedness Measures, Ve = Vegetation, S = Slope, C = ground squirrel SDM, and E = Eastness. The (*) indicates a random slope was applied to the variable.

Explanatory Variables	AIC	ΔAIC
Vr/Ve/S*/E*	41603.1	0
Vr*/Ve/S/E*	41706.3	103.2
Vr/Ve/S/E*	41716.6	113.5

4.3.2. Final Model Results

The final model included variables VRM, vegetation, slope and eastness, with a random intercept for Individual ID and random slopes for eastness and slope represented by Equation 5 (Table 10).

$$w(x) = \exp\begin{pmatrix}(0.058)VRM + (0.215)Slope + (-0.25)Eastness + (0.049)Shrub + \\ (-0.729)Tree + (-1.022)Developed + (0.004)Water\end{pmatrix} \quad (5)$$

Table 10 - Final RSF model covariate point estimates, standard errors, and 95% CIs.

Explanatory Variables	Estimate	Std. Error	Lower 95% CI	Upper 95% CI
(Intercept)	2.017	0.176	1.671	2.363
VRM	0.058	0.013	0.034	0.085
Slope	0.215	0.051	0.116	0.315
Eastness	-0.25	0.046	-0.341	-0.159
Shrub*	0.049	0.04	-0.028	0.127
Tree	-0.729	0.256	-1.231	-0.228
Developed	-1.022	0.142	-1.3	-0.745
Water*	0.004	0.41	-0.799	0.806

*Variable not significant due to 95% CI overlapping zero.

The majority of the variables included in the final model were informative to non-adult golden eagle resource selection. This was determined because the point estimates' 95% CIs did not include zero (Table 10). The variables VRM (0.058 ± 0.034 to 0.085) and slope (0.215 ± 0.116 to 0.315) positively influenced resource selection and the variable eastness (-0.25 ± -0.341

to -0.159) negatively influenced resource selection. Within the vegetation variable, the “Tree” and “Developed” categories negatively influenced resource selection compared to the “Herbaceous” category. The vegetation categories “Shrub” and “Water” when compared to the “Herbaceous” category were uninformative as the 95% CIs overlapped zero (Table 10).

To test the model predictive capacity and reliability, the LOOCV analysis was conducted. The resulting relative predictive strength of the model was 0.62, indicating the model had poor predictive capacity. The final model was tested to determine if the model assumptions were adequately met by evaluating simulated residuals for zero inflation, overdispersion, and heteroscedasticity using the *DHARMa* package in R (Hartig 2018). These results were statistically insignificant which indicated that the residuals were not zero-inflated (p-value = 0.076) or over-dispersed (p-value = 0.994). However, there were signs of heteroscedasticity meaning that the model estimates may not be precise and should be interpreted with extreme caution (Figure 47**Error! Reference source not found.**). Based on the poor relative predictive strength of the model, and the violation of the heteroscedasticity assumption, the results of this analysis were not analyzed further.

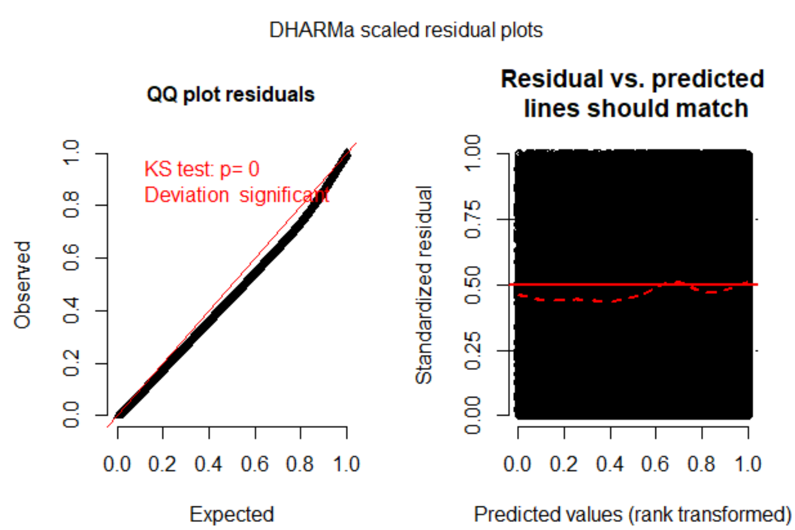


Figure 47 - QQ and residual plots used to evaluate the potential for heteroscedasticity within the simulated model. Because the data do not match the predicted lines, it demonstrates that there was some heteroscedasticity within the residuals.

4.4. Discussion

As indicated by the results from the LOOCV, and violation of heteroscedasticity assumption, the RSF model developed for non-adult golden eagle did not perform well. Because of this, these results cannot be applied to non-adult golden eagles outside of this study and should be interpreted with extreme caution for the individuals within this study. The primary goal of this analysis was to assess if ground squirrel distribution influenced non-adult golden eagle resource selection. As a result of poor model performance, the influence of ground squirrel distribution on non-adult golden eagle resource selection is unknown. While the results of this analysis indicate that the distribution of ground squirrels did not influence individuals within this study, these results should be taken with caution because the violation of heteroscedasticity assumption; while it does not bias the model, it does result in less precise estimates.

There are several additional reasons why the ground squirrel distribution variable may not have been included within the final model. First, the way the variable was used may not have been the best way to evaluate this relationship. The ground squirrel distribution variable used the logistic output without additional transformations or manipulations, and relative probability may not have provided enough differences between high and low values to capture differences in selection. Converting this variable into a binary format using a cutoff point may have yielded improved results. Furthermore, the variable was only able to indicate the relative probability of ground squirrel occurrence based on burrow presence, but the overall abundance of individuals may be a more important metric for golden eagles within the Altamont (Hoover 2002). Additionally, it may have been better to analyze in terms of distance from the patch as the literature indicates there seems to be a distance in which an eagle will forage in relation to ground squirrel burrows (Smallwood et al. 2009). Finally, the distribution of ground squirrels will likely have some variation by year, and this study was not able to capture the potential expansion and contraction of the species' yearly physical distribution (e.g. if removal efforts were limiting distribution).

The variables included within the final model were consistent with the findings of other studies evaluating golden eagle resource selection. Increases in terrain heterogeneity and slope angle were positively associated with non-adult golden eagle resource selection (Smallwood et al. 2009, Watson, Duff, and Davies 2014, Lebeau et al. 2015). The eastness variable was negatively associated with non-adult golden eagle resource selection, meaning non-adult golden eagles selected against more easterly slopes. Considering that the prevailing wind direction at the Altamont included northwest and southwest winds, it is likely that the non-adult golden eagles were selecting for smoother wind patterns of westerly facing slopes (Smallwood and Karas 2009). Within the vegetation categories, avoidance of Development was consistent with other studies conducted at the Altamont (Hunt 2002, Wiens et al. 2018). While these variables were similar to those found in other studies, these preferences may not hold true for other individuals outside of this study and the level of effect for individuals within this study should be interpreted understanding the aforementioned caveats.

Because the model had low predictive performance, it is likely that there were other factors influencing resource selection which were not captured within this analysis. Some of these influences may be related to interactions among territorial individuals and non-adult golden eagles, wind patterns, or even additional nested effects this study was not able to explore (e.g. sex, season, year). This study was unable to capture actual wind speed and wind patterns which could likely influence flight (e.g. higher wind speeds). While orographic lift and eastness were considered, neither of these two variables were associated with actual wind conditions that can be detected during finer scale analyses (e.g. field-based behavior studies).

Additionally, this analysis only used one random effect level, the individual, and there may have been other factors influencing resource selection such as age, sex, and season. There were also large differences in the number of points between individuals which may have reduced the LOOCV score, where individuals with fewer points may not be able to adequately predict individuals with more points. One other limitation of this study was that all variables were assessed at the 30m resolution and were derived from remote sensing techniques which come with some level of inherent error. With finer resolution information, some of the variables may have been better suited. Additional studies should be conducted to further analyze the effects of prey on golden eagle resource selection which can improve upon this analysis.

Chapter 5 Spatiotemporal Pattern Mining to Examine Non-Adult Golden Eagle Use

In addition to understanding the resource selection by non-adult golden eagles, understanding the spatiotemporal trends in the study area can identify where important localities of resources may exist on the landscape. Space-time pattern mining tools are useful for analyzing patterns of use that are not apparent with a visual inspection of data alone (Baas 2013). Additionally, these trends can identify where frequently used locations by golden eagles occur and indicate if there are differences in spatial use patterns of golden eagles over time (e.g. shifting) (Sarkar et al. 2015). Trend analysis can be used to effectively demonstrate individual(s) preferences in space use, as well as differences in monthly, seasonal, or yearly variation in use.

The data collected as part of the telemetry study provides a unique opportunity to evaluate the space used by non-adult golden eagles within the Altamont. This data set contains individuals that are representative of different age classes that originate from different temporal strata (Figure 38). Because of the temporal distribution of the dataset (e.g. six years), it is possible to use space-time pattern analyses to determine if there have been consistently used areas within the study area. In this chapter, the non-adult golden eagle telemetry data is analyzed for both spatial and temporal patterns of use within the study area. Pattern exploration and visualization techniques provided by ArcGIS Pro were used to explore trends in data including hot spot analysis, the STC Explorer add-in, and emerging hot spot analysis (EHSA).

5.1.1. Spatial and Temporal Hot Spot Analysis

Pattern exploration using the hot spot analysis aggregates the data into spatial bins organized into a grid of square or hexagon cells. Each bin is assigned a value (count) based on the total number of occurrences within that bin (Bass 2017). The Getis-Ord Gi* statistic evaluates the reference bin in relation to a surrounding neighborhood. The statistical significance of each bin is determined by the bin having a high or low count and having a spatial relationship to nearby bins that also have either high or low counts. The bin and neighborhood counts are compared to the average count across all bins. If the localized count is higher or lower than expected, the bin is given a statistically significant z-score. The results of the hot spot analyses are interpreted using the z-score and p-value. Larger positive or negative z-scores indicate hot or cold spots respectively. Lower p-values imply increased confidence in the pattern not resulting from random chance.

The neighborhood setting is highly dependent on the question being explored. Different neighborhood settings can greatly alter the spatial pattern being evaluated (Bach et al. 2014). For example, if the question is to understand crime rates in a city, the spatial neighborhood may aggregate data by city block to understand differences in neighborhoods. However, if the question is analyzing number of birds killed per wind turbine, data may be evaluated by turbine or turbine string. By carefully considering the question at hand, hot spot analyses can provide useful information regarding the system being investigated (Sakar et al. 2015, Baas 2013).

Space-time cubes (STC) provide a framework to evaluate spatial and temporal trends within data by aggregating points into explicit spatiotemporal bins. Bins are generated by evaluating and combining data that are within similar spatial (XY) and temporal (Z) strata as shown in Figure 48 (Bach et al. 2014). There are several programs that can be used to create and visualize STCs such as Tardis, Cubix, and Esri's ArcGIS Pro. While there are several programs that can generate STCs, the STC tool in ArcGIS Pro provides a user-friendly interface with several online resources and training opportunities. Thus, to evaluate the non-adult golden eagle telemetry data, this study used the STC tool in ArcGIS Pro.

To create a space-time cube, a layer of events (points), each associated with a time, is needed as input. The user selects appropriate spatial and temporal neighborhood sizes and a time step alignment point, essentially a starting point, so that data can be aggregated into bins creating a 3D spatiotemporal grid. The “Bin Time Series”, also referred to as a location or stack, in the temporal binning structure of the data cube. Individual rows in the data cube represent a time slice. The individual boxes represent a distinct cluster of data points are then counted by bin and then evaluated across bins and time slices (Bach et al. 2014).

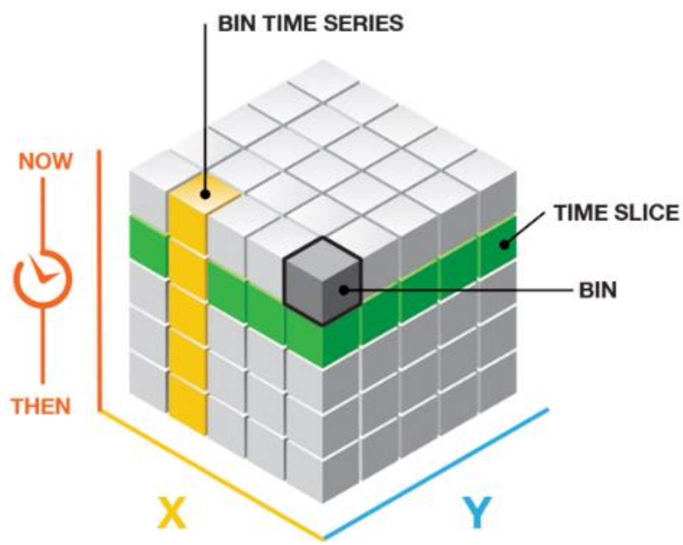


Figure 48 - Example of how data are binned and analyzed within an STC. Source: https://pro.arcgis.com/en/pro-app/tool-reference/space-time-pattern-mining/create-space-time-cube.htm.

Emerging Hot Spot Analysis (EHSA) is a derivative of the hot spot analysis that uses the STC binning structure for aggregating data. Each bin is given a value using the Getis-Ord Gi* statistic as described above. The Mann-Kendall statistic evaluates the data set to identify space-time correlation within each vertical stack of the STC (Bass 2017). Temporal periods are sequentially evaluated within the stack. Each reference temporal period (*t*) is given ±1 if the count in the $t+1$ time period is either higher or lower. A value of zero is given to *t* if there is no difference between the *t* and the $t+1$ temporal period. Statistical significance is determined by evaluating the sum of the stack compared to the expected sum (zero). Based on this evaluation, each temporal period is given a z-score and p-value. Larger positive or negative z-scores indicate hot or cold spots (Figure 49). Lower p-values imply increased confidence in the pattern not resulting from random chance. The EHSA then classifies spatial hot and cold spots into 17 categories. The full set of possible categories is shown in Appendix B. These values provide information on the spatiotemporal trends within the data.

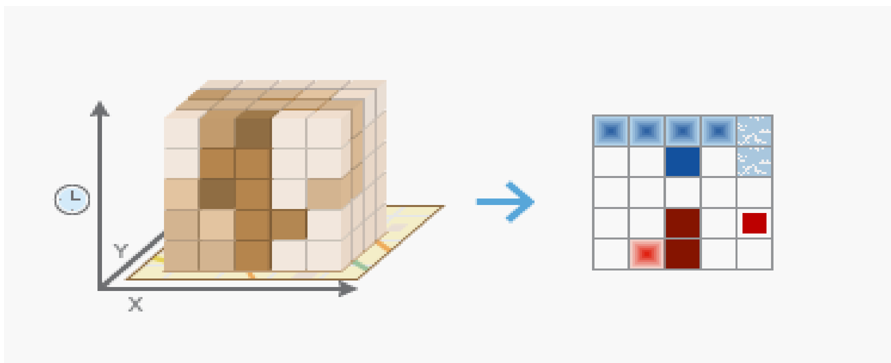


Figure 49 - Conceptual diagram for an emerging hot spot analysis. The space-time cube neighborhoods are evaluated based on spatial and temporal neighbors to find hot (red) and cold (blue) spots within the data. Source: http://desktop.arcgis.com/en/arcmap/10.3/tools/space-time-pattern-mining-toolbox/emerginghotspots.htm.

Similar to the hot spot analysis, neighborhood settings can greatly alter the trend being compared and these choices are highly dependent on the question being explored (Bach et al. 2014). For example, if the question is to understand how often nests fail over several years, the temporal neighborhood may aggregate data by year and some distance function incorporating individual territory size. However, if the question is analyzing the frequency of movement within an individual’s home range, data may be aggregated by the hour or day and then compared against the relevant subsets of a territory. By carefully considering the question at hand, these tools can provide very useful information regarding the system being investigated (Sakar et al. 2015, Baas 2013).

5.2. Methods

The Pattern Mining toolbox in ArcGIS Pro 2.2 was used to analyze the spatiotemporal trends of 16 non-adult golden eagles within the study area. The first step of this analysis was to generate a hot spot analysis to evaluate the spatial clustering of non-adult golden eagle use. Then to explore spatiotemporal trends, a STC was developed using the non-adult golden eagle telemetry data. An emerging hot spot analysis was conducted using the STC binning structure and visualized in 3D using the STC Explorer. By varying the spatial and temporal neighborhoods, emerging hot spot analyses were used to evaluate seasonal, yearly, and multiyear trends in space use of the study area by non-adult golden eagles. The following sections provide the analytical methodology used for the development of the hot spot analysis, STC hot spot analysis, and EHSA analyses.

5.2.1. Neighborhood Settings

When evaluating spatial and temporal patterns, in this case non-adult golden eagles, it was critical to determine effective spatial and temporal neighborhoods that were appropriate for the system being evaluated (Baas 2013). The data used in this study included both perch and non-perch locations. When aggregating data, emphasis was placed on choosing data aggregation settings adequate to explore differences in spatial and temporal use. To identify an adequate spatial neighborhood, the information within the telemetry data was used to evaluate patterns in use.

The average distance between fixes (15-minute intervals) across all individuals was calculated and used to identify a spatial aggregation neighborhood given that both stationary and non-stationary points would be evaluated. The average distance between fixes was approximately 1,100m. However, for simplicity, a distance of 1,000m was used to establish the spatial neighborhood for point aggregation in each analysis. There were two options for aggregation shapes available for the spatial and temporal analyses used in this study: fishnet (rectangle) and hexagon grids. Because the study area has several uneven and irregular shaped segments, the hexagon grid was selected. The hexagon shape appeared to fit the irregular pattern of the study area better than the fishnet grid minimizing edge effects. The size of hexagons, the distance across a cell, was set to 1,000m. The same hexagon grid was used in the hot spot analysis, STC hot spot analysis, and EHSA.

Distances for evaluating spatial and temporal hot spots were measured from the centroid of each hexagon and the spatial neighborhoods included all hexagons that fell at least partially within the stated search radius. Best practices developed by Esri (2018) recommend that neighborhoods should not be too small, resulting in no trend detection, or too large, resulting in overly optimistic results. Essentially, users are looking for the “Goldilocks” scenario. Within the optimal range there are likely multiple combinations of appropriate spatial and temporal neighborhoods. Because there have been few wildlife studies published to serve as a guide for this approach, distance thresholds used in this analysis were based on the size of the study area.

Because there are likely multiple scales at which patterns can be detected, this study used small and large spatial neighborhoods for hot spot evaluation based on the study area dimensions. In analyzing the study area, the average distance from east to west was approximately 10,000m, or 10 hexagons, and the average distance from north to south was approximately 20,000m, or 20 hexagons. For this study, the small distance band for each analysis was set to 3,000m which included three spatial neighbors outward from the cell of interest and represented three average interval distances calculated from the telemetry data. The large spatial neighborhood distance was set to 5,000m which included five spatial neighbors outward from the cell of interest and represented five average interval distances. It was felt that if less than 3,000m was used, it may be too fine scale to detect a trend and if larger than 5,000m was used, some places would not contain sufficient neighbors.

5.2.2. Hot Spot Analysis Settings

Spatial clustering of non-adult golden eagle points across the study area was evaluated using a hot spot analysis in ArcGIS Pro. As discussed in Section 5.2.1, the aggregation distance used to compile points was a grid composed of 1,000m hexagons. This analysis used non-adult golden eagle telemetry data from 16 individuals totaling 57,249 points that represented both stationary and flying points. Hot spot trends were evaluated using the 3,000 and 5,000m distance bands.

5.2.3. Space-Time Cube Settings

There were four critical settings for the STC development which included spatial neighborhood, temporal neighborhood, aggregation bin shape, and time step alignment. To evaluate spatiotemporal trends of use in the study area, data were aggregated by the count of points per bin. There were varying date and time formats within the dataset, so an additional “Date” field was added to the attribute table to standardize the format of the time information. When all the individuals were included (n=16), there were a total of 57,270 points representing approximately six years. The temporal distribution of the data ranged from December 29, 2012 to December 5, 2018. To limit the start time bias among bins, data for the month of December 2018 were removed, which accounted for 21 points. The adjusted data time frame then included December 29, 2012 to November 26, 2018 which was the closest timeframe achievable to limit start and end time bias. The final number of points used was 57,249 points.

As a result of the adjusted end time of the dataset, the time step alignment was set to "start time", where data aggregation started with the month of December 2012 and ended at November 2018. Setting the temporal neighborhood was based on the transmitter deployment timeframes and the time step alignment. Due to inconsistent start dates for when transmitters were deployed, a time step interval of one month was used. Additionally, by selecting the one-month time interval, it allowed for different temporal analyses when incorporated into an EHSA.

Once the STC was generated, a STC hot spot analysis was conducted using a 5,000m spatial neighborhood and considered one temporal neighbor. This step was completed to understand the distribution of hot spots in space and time. The STC Explorer add-in in ArcGIS Pro 2.2 was used to visualize the STC hot spot analysis. This tool created a 3D representation of the STC hot spot analysis and allowed for manipulation of row and column visibility to better explore the data pattern structure. The results of this visualization made it possible to explore various patterns within the cube that explain both the necessity and the results of the EHSAs. The 3D representations included visualizing data by z-score, hot spot classes, count, and significance of relationship.

5.2.4. Emerging Hot Spot Analysis Settings

The EHSA uses a STC stored in a netCDF file to analyze spatiotemporal trends by evaluating patterns within data across multiple spatial and temporal neighborhoods. The settings required for this analysis included choosing the spatial neighborhood, temporal neighborhood, and an evaluation criterion to compare the neighborhood analysis. Much like the STC, how the settings are selected depends on the system being evaluated, but should be in terms that are relevant to that system (Bach et al. 2014). For this analysis, trends were analyzed using the two spatial neighborhoods discussed in Section 5.2.1 and three temporal scales to evaluate the patterns of use by non-adult golden eagles within the study area.

The spatial neighborhoods used included both smaller and larger numbers of spatial neighbors as described in Section 5.2.1. To ensure that this search neighborhood would be used consistently across the analysis, the "fixed distance" option was selected for conceptualizing spatial neighborhoods. Temporal neighborhoods were set at scales in which there may be underlying patterns based on the biology of the species. Because the STC was binned using a monthly time interval, there were several temporal scales that could be evaluated. For this analysis, the temporal neighborhoods selected included season, year, and multiyear neighborhoods. Because the STC was binned by month, these neighborhoods were calculated using the number of months in each time period. Seasonal trends, or three-month windows, were evaluated to determine if the patterns of use varied by important life history events (e.g. migration, dispersal). The yearly, or 12-month, temporal neighborhood was used to evaluate potential differences in use across all telemetry years. The multiyear time step was set to three years, or 36 months, based on various clusters of deployed transmitters (e.g. when several transmitters were deployed at the same time) (Figure 38).

5.3. Results

The result from the hot spot analysis, STC hot spot analysis, and EHSA provided useful information regarding the trends in non-adult golden eagle use within the study area. Using the 1,000m grid cell size, 260 hexagons, shown in Figure 50, were created. The following subsections present the results of each analysis. First, the results of the spatial hot spot analyses are reviewed. Then the results of the STC hot spot analysis are presented and visualized in 3D using the STC Explorer. The final section presents the results from the EHSA analyses regarding differences in spatial and temporal neighborhoods.

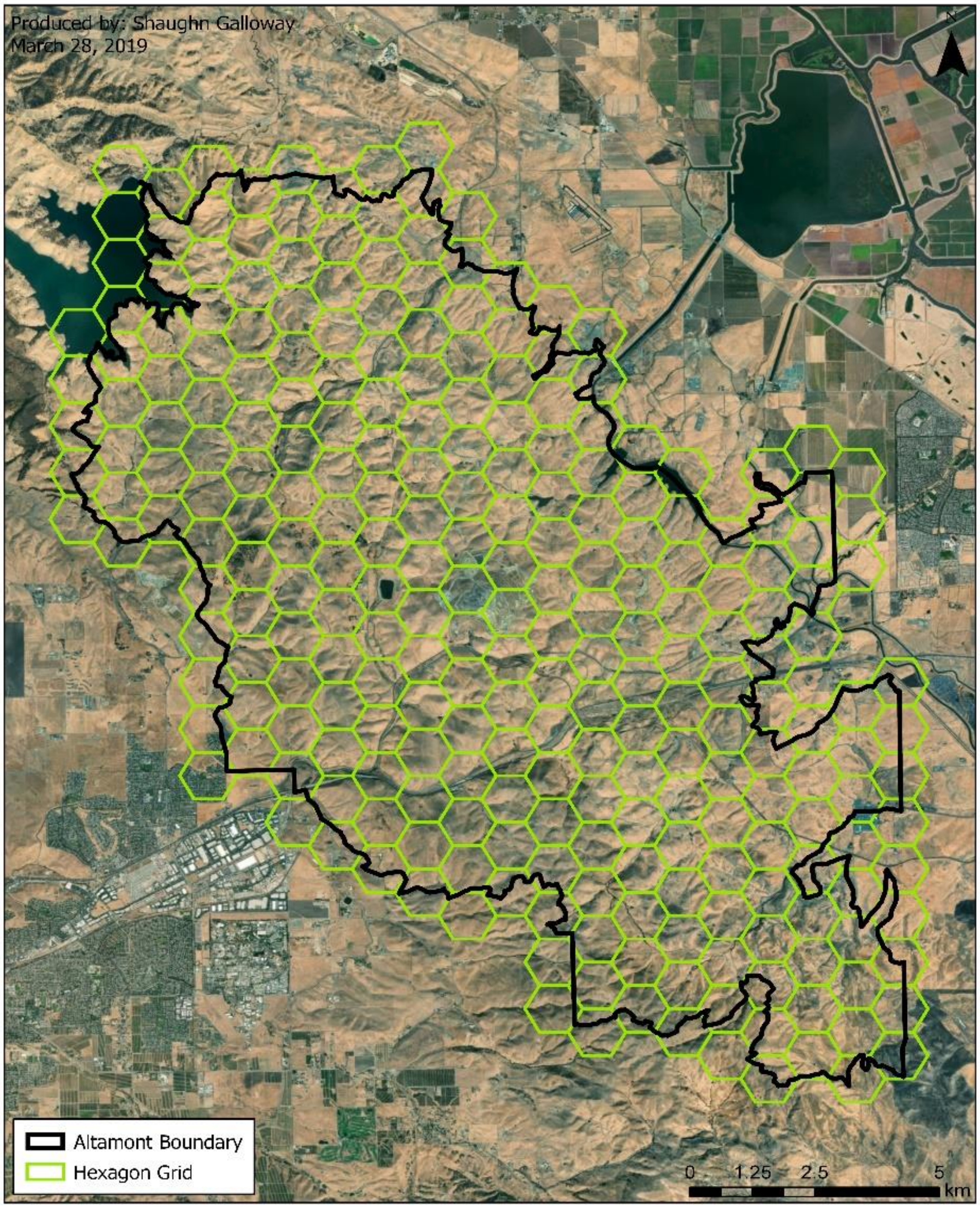


Figure 50 - Hexagon grid used in the hot spot analysis, STC hot spot analysis, and EHSA. Altamont boundary provided by Doug Bell and Lee Neher.

5.3.1. Hot Spot Analysis

The results of the hot spot analysis at the 3,000 and 5,000m neighborhoods (Figure 51) varied in patterns detected. At the 3,000m spatial neighborhood scale, only hot spots and non-significant trends were identified. The statistically significant hot spot cells occurred mostly in the north-central region of the study area (Figure 51), however, the majority of the cells did not have a statistically significant trend. The 5,000m spatial neighborhood scale identified a range of statistically significant hot and cold spots (Figure 51). Similar to the 3,000m scale, statistically significant hot spots at the 5,000m scale occurred in the north-central region of the study area. The statistically significant cold spots occurred within the southern region of the study area (Figure 51). The not statistically significant cells represented an approximately four cell wide band between the statistically significant hot and cold spots.

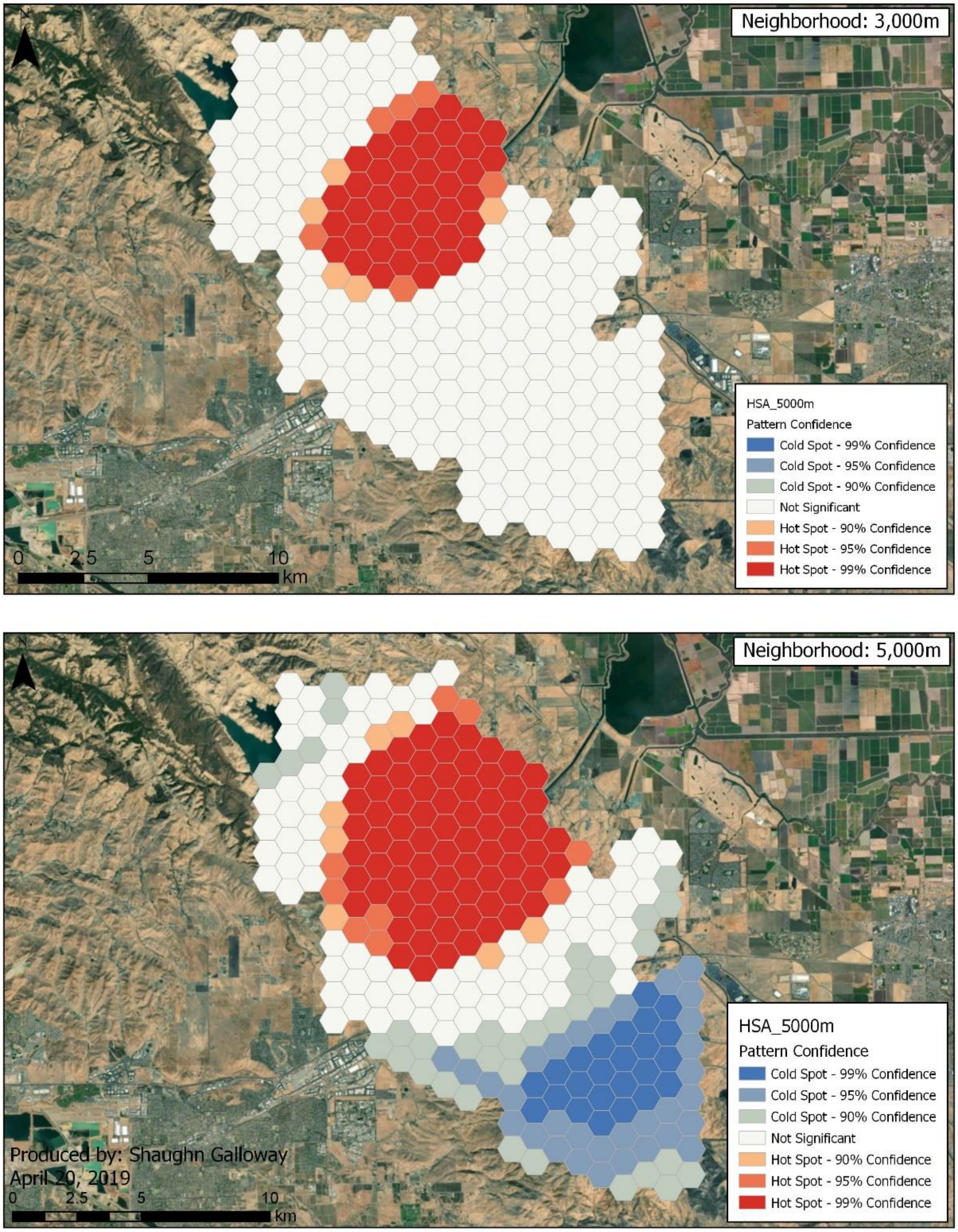


Figure 51 – Results from the spatial hot spot analysis using the 3,000 and 5,000m spatial neighborhood settings.

5.3.2. Space-Time Cube Hot Spot Analysis

The STC hot spot analysis result showed only hot spots or not statistically significant trends. Figure 52 shows the spatial and temporal distribution of hot spots and Appendix B includes additional images of the cube viewed at different aspects and highlighting various patterns (e.g. hot spots). The majority of the hexagons within the STC hot spot analysis were not statistically significant. Using the STC Explorer for visualization, the spatial distribution of the not statistically significant cells was consistent throughout the study area. The temporal distribution of statistically insignificant cells was more consistent in the southern region of the study area. However, in the north-central region of the study area, insignificant cells were intermixed with periods of the statistically significant hot spots. Following March 2017 there, there were no statistically significant cells.

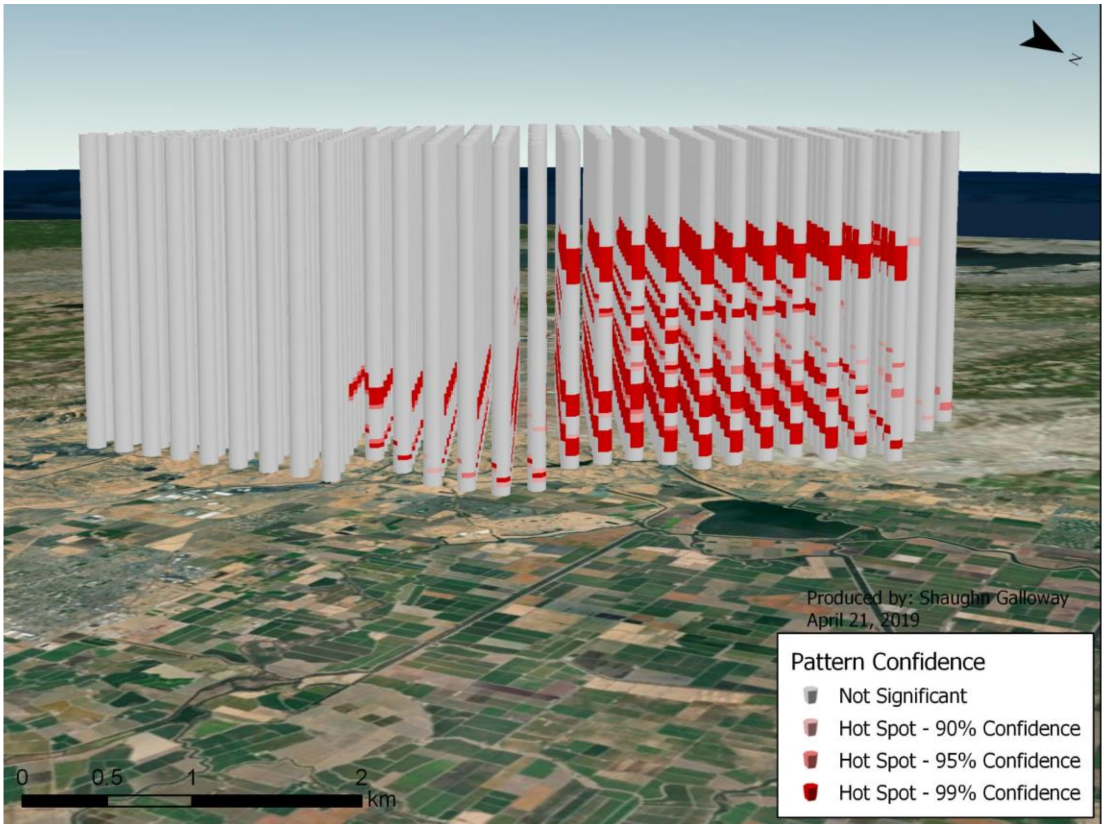


Figure 52 – Pattern distribution across the study area. Viewed from the east.

The spatial distribution of hot spots occurred more or less continuously through the study area, with the exception of the far southern region of the study area as demonstrated in Figure 53. Statistically significant hot spots occurred in distinct temporal bands across the study area. However, the temporal bands occurred at higher densities in the north-central region of the study area (Figure 52 and Figure 53).

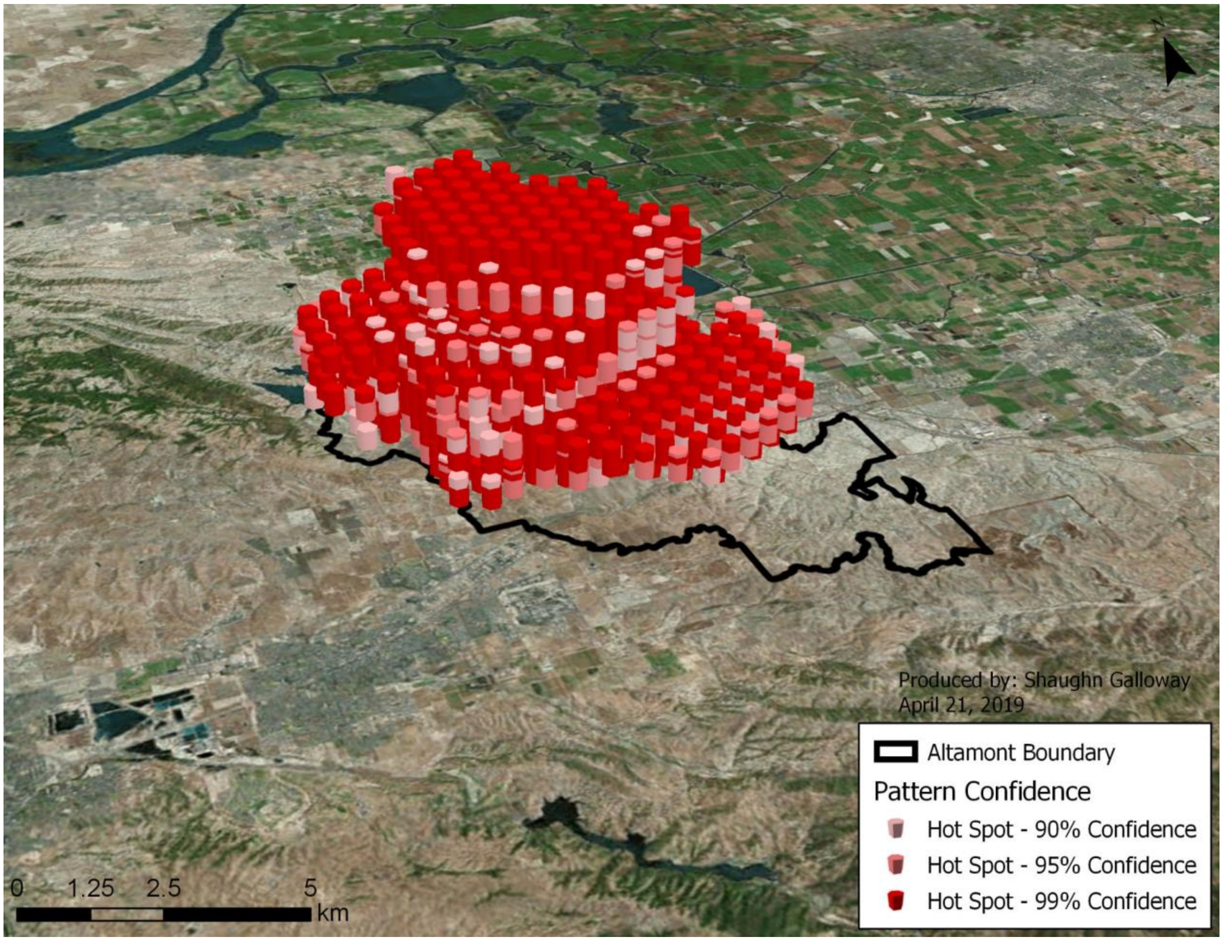


Figure 53 – Spatial distribution of statistically significant hot spots. Viewed from the southwest. The statistically insignificant cells shown in Figure 52 were removed to better visualize the hot spot patterns. Altamont boundary provided by Doug Bell and Lee Neher.

Regarding the temporal patterns within the STC hot spot analysis, there are several obvious patterns of use visible. As can be seen in Figure 52, significant hot spots did not begin to develop in the study area until the March to April 2013 time slice (three layers from the bottom) and did not occur after the February to March 2017 temporal band (last red layer in Figure 52). Between the start and end dates, there were sporadic patterns of use, but four major temporal clusters were present: March 2013 to October 2013, December 2013 to June 2014, March to December 2015, and June 2016 to February 2017 (Figure 52). However, the March to December time period was associated with more sporadic use. While the data continues into November 2018, the frequency of use was not significant enough to standout as statistically significant hot spots. This is likely because the number of points within these cells is less than 16 per cell, much less than in cells in earlier monthly time slices.

5.3.3. Emerging Hot Spots Analysis

The results of the EHSA revealed patterns in non-adult golden eagle use within the study area. Generally, the patterns in site use were consistent among the spatial neighborhoods evaluated (3,000 and 5,000m) within each temporal neighborhood evaluated (e.g. season). The following subsections present the results of each EHSA by temporal neighborhood (seasonal, yearly, and multiyear), and compare and contrast the spatial neighborhoods evaluated (3,000 and 5,000m) within this analysis.

5.3.3.1. EHSA of Seasonal Neighborhoods

The EHSAs evaluating the seasonal trends in non-adult golden eagle use were unable to identify statistically significant patterns at the 3,000 or 5,000m spatial neighborhoods. This result is shown in Figure 54, where all of the hexagons are white indicating no pattern.

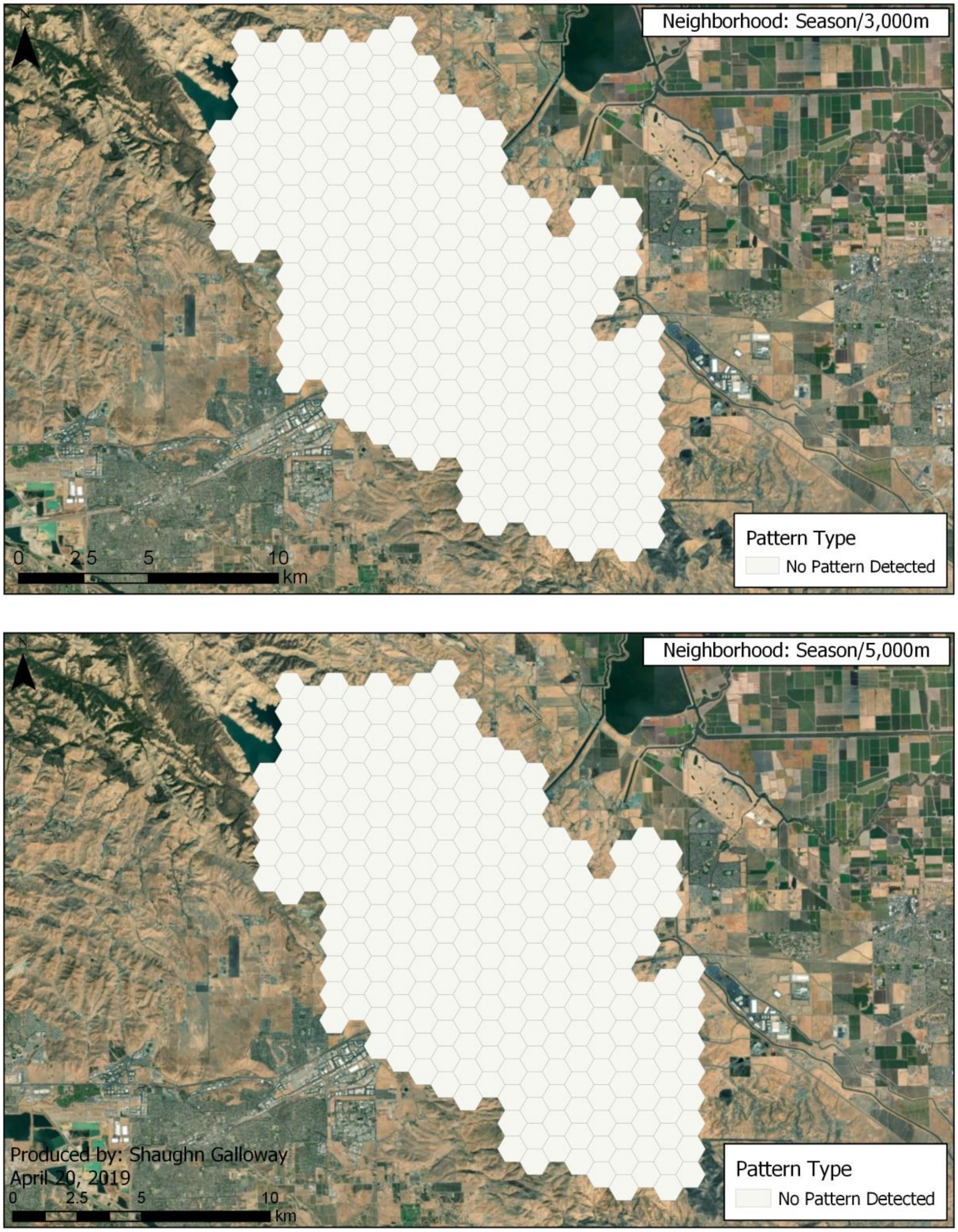


Figure 54 – Results of the EHSA evaluating differences in seasonal trends.

5.3.3.2. EHSA of Yearly Neighborhoods

The results of the EHSA analysis in the yearly temporal neighborhood identified only no pattern or cold spots. At both spatial neighborhood scales, the majority of cells fall into the Oscillating Cold Spot category and these cells are located in the north-central portion of the study area (Figure 55). In the 5,000m analysis scale, this oscillating cold spot extends further south and there are fewer cells with no pattern detected (Figure 56).

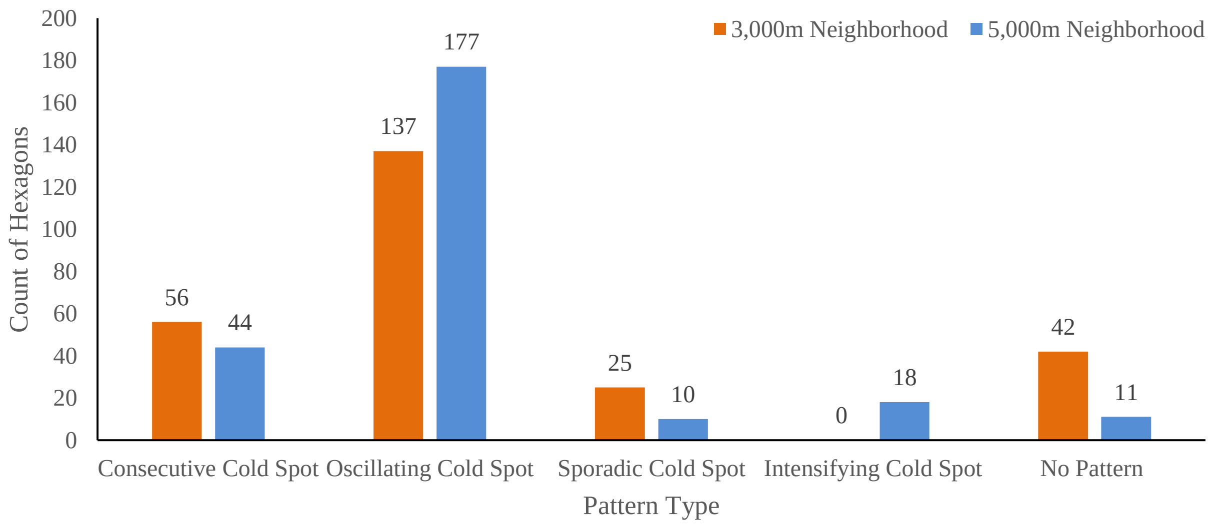
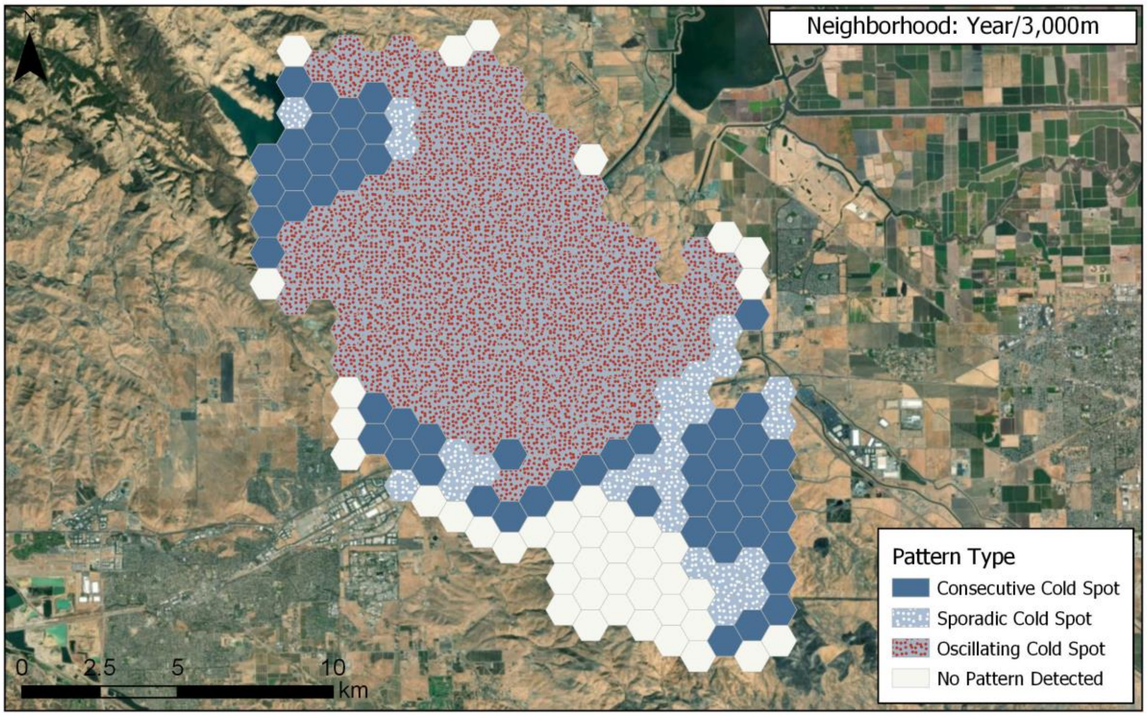


Figure 55 – Counts of hexagons in various hot and cold spot patterns found in the 3,000 and 5,000m analysis scales for the yearly EHSA.



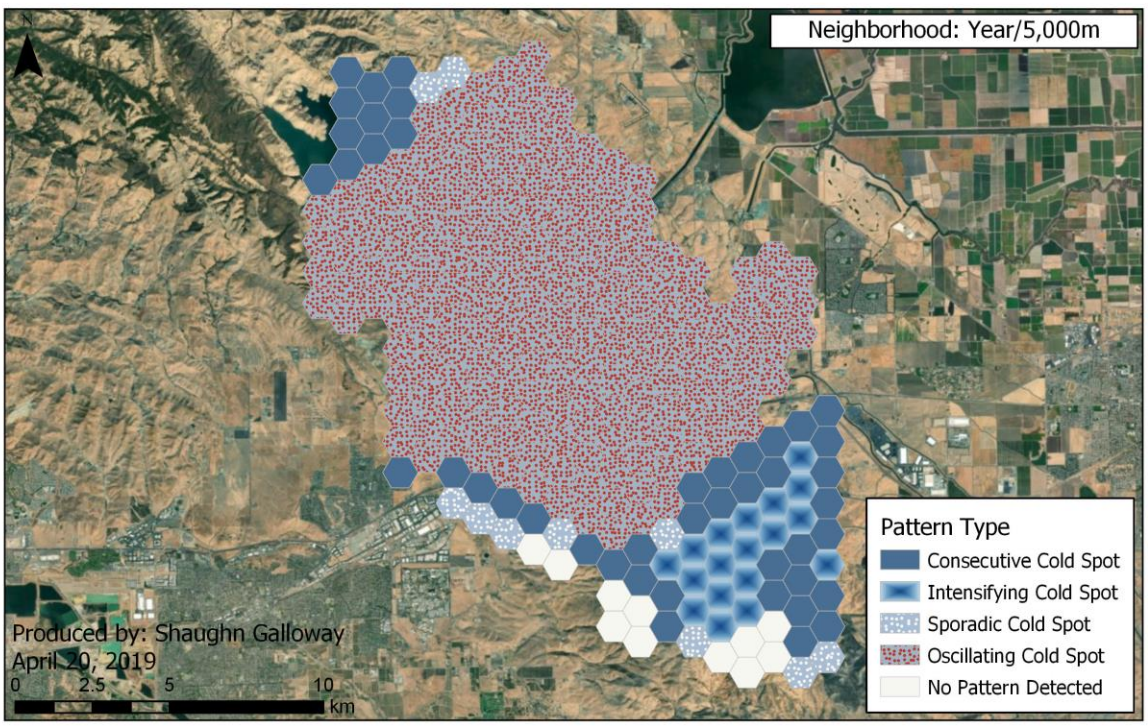


Figure 56 - Results of the EHSA using a yearly temporal neighborhood and both 3,000 and 5,000m spatial neighborhoods.

5.3.3.3. EHSA of Multiyear Neighborhoods

The multiyear temporal neighborhoods resulted in the greatest diversity in number of pattern categories and spatial distribution of patterns. At the 3,000m spatial neighborhood scale, there was a total of nine patterns with the bulk of the hexagons occurring within the Consecutive Cold Spot (n=107) and Oscillating Cold Spot categories (n=94) (Figure 57**Error! Reference source not found.**). However, both hot and cold spots were identified at this neighborhood level. There were five types of hot spots that occurred within the study area with the majority of the data being classified into Intensifying Hot Spot (n=18), Diminishing Hot Spot (n=7), and Persistent Hot Spot (n=5) categories (Figure 57**Error! Reference source not found.**).

The 5,000m spatial neighborhood identified a total of 11 patterns, and similar to the 3,000m neighborhood, the majority of the cells are Oscillating Cold Spot (n=106) and Consecutive Cold Spot (n=60) categories (Figure 57). Like the smaller neighborhood size, there are five types of hot spots within the study area which are dominated by Diminishing Hot Spot (n=30), Persistent Hot Spot (n=15), and Historical Hot Spot (n=4) categories.

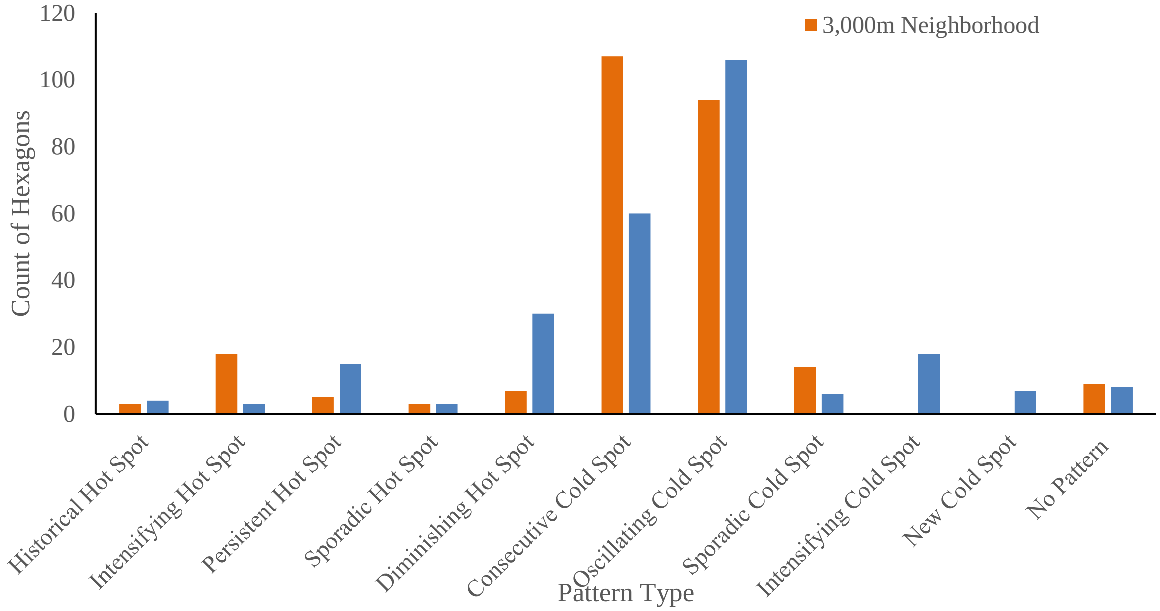


Figure 57 - Counts of hexagons in various hot and cold spot patterns found in the 3,000 and 5,000m analysis scales for the multiyear EHSA.

There were similarities within the spatial distribution of both hot and cold spots between the different spatial neighborhoods evaluated (Figure 58). The majority of the hot spot cells occur within the north-central region of the study area and become fewer as distance increases from this region to the west and south. At the 3,000m scale, there are fewer hot spot cells altogether. The 5,000m neighborhood analysis had similar categorical distribution and spatial arrangement to the 3,000m analysis (Figure 57 and Figure 58). However, the distribution of each pattern extended further to the south and west in the 5,000m analysis.

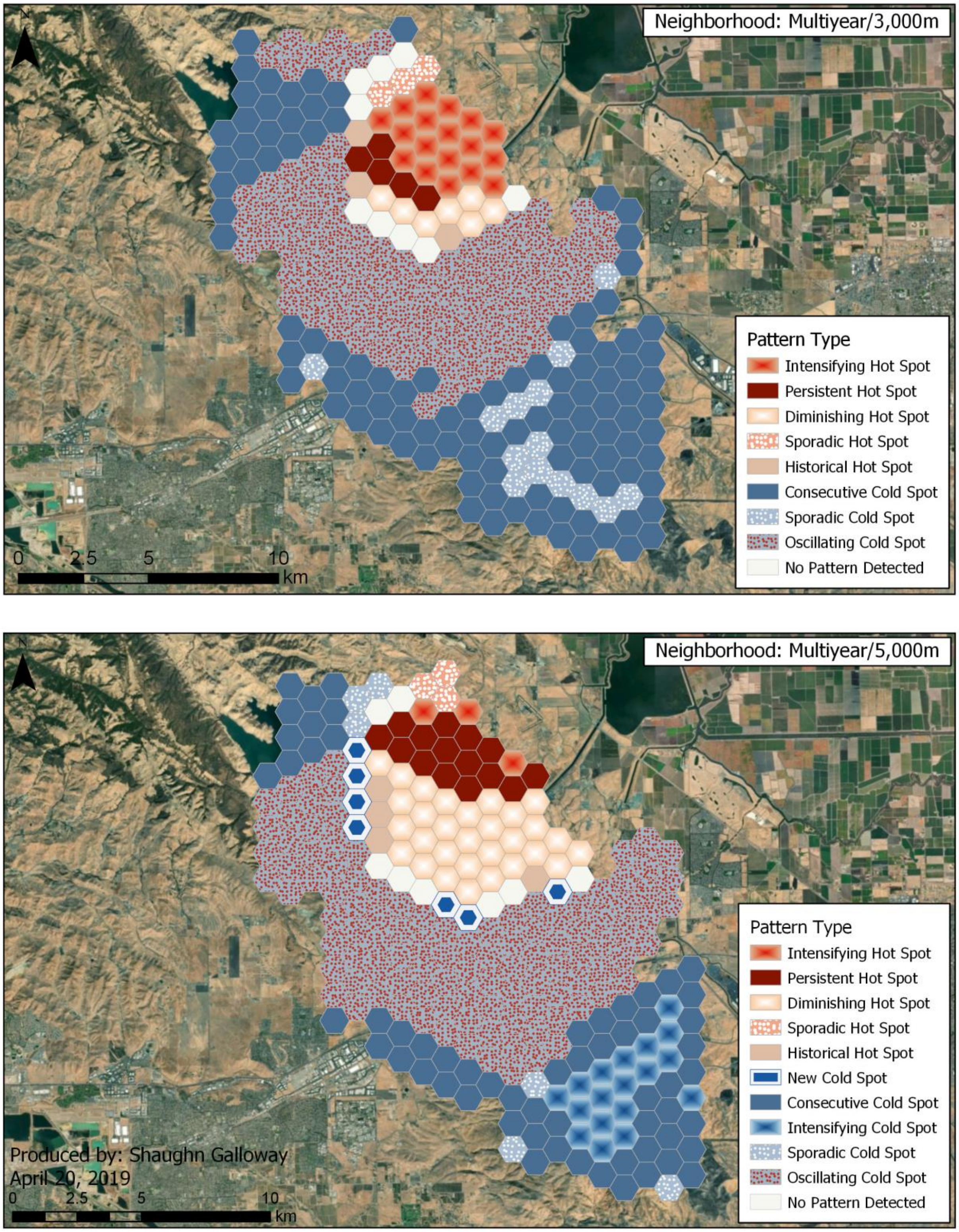


Figure 58 - Results of the EHSA using a multiyear temporal neighborhood and both 3,000 and 5,000m spatial neighborhoods.

5.4. Discussion

The results of the hot spot analysis, STC hot spot analysis, and EHSA provide useful information regarding the trends in the use of the study area by non-adult golden eagles. The most interesting trends within the hot spot analyses were the statistically significant hot spots occurring in the north-central region of the study area. In the time periods prior to March 2017, this trend was also apparent in the STC hot spot analysis. The EHSA multiyear analysis also identified the north-central portion of the study area as being a statistically significant hot spot. However, the hot spots in the north-central portion of the study area were not present in either the seasonal or yearly EHSA analyses. What this pattern is likely demonstrating, is that the north-central region of the study area was historically significant to the individuals within this study. However, due to the reduction of both number of individuals with transmitters and activity following March 2017, the finer temporal scales did not have sufficient neighborhoods to identify these locations as statistically significant hot spots. The lack of patterning at the seasonal scale is likely because the individuals were accessing the study area either in low frequency throughout the year and/or activity was spatially dispersed to the point that the three-month temporal neighborhood was too fine of a scale to identify statistically significant trends.

The year and multiyear temporal neighborhoods produced predominantly “Oscillating Cold Spots”. “Oscillating Cold Spots” indicates that the cell is a statistically significant cold spot in the final time step of the analysis, but was a statistically significant hot spot during other time periods. The large amount of oscillating cold spots within the year and multiyear temporal neighborhoods is attributed to the large number of statistically insignificant cells from March 2017 to November 2018, as can be seen in the 3D visualizations of the cell columns in Figure 52. This temporal range between March 2017 to November 2018, coincided with the addition of six non-adult golden eagles newly equipped with transmitters starting in approximately March 2017 and the reduction in the number actively transmitting individuals from earlier time periods (see the timelines in Figure 38). The newly equipped individuals were predominantly within the hatch year class (n=4) and were more likely to disperse outside of the study area during this time period. This factor likely influenced the low number of fixes during this time period and high numbers of statistically insignificant cells and Oscillating Cold Spots in the season and yearly analyses.

In the EHSA analyses, there were similar results between the 3,000 and 5,000m scales within their respective temporal neighborhoods. Differences in patterns were mostly associated with the level of hot spot and distribution of cold spots. Statistically significant hot spots only show up in the multiyear temporal analysis and were present in both the 3,000 and 5,000m spatial neighborhoods. The multiyear analysis used a three-year time span. These temporal periods happened to occur when the majority of the non-adult golden eagles, equipped with transmitters, had access to the project area. Hot spots are present in the multiyear analysis because the elongated time frame encompassed the majority of the data. This result was similar to the hot spot analysis, shown in Figure 51, which considered the entire dataset regardless of time.

Both spatial and temporal patterns of frequent use diminish in cells further south and west of the north-central cluster. While not a part of this analysis, the north-central region of the study area could be evaluated for site-specific conditions that may result in increased use of this region compared to the southern portion of the study area (e.g. more favorable abiotic conditions). Due to the age class of individuals at the end of the study period, it is unknown if this area plays a significant role for all the individuals in this study. However, because individual golden eagles were occupying the north-central region of the study area while acting independently of one another over time, this potentially highlights the importance of this area for other individuals in the non-adult or floater population.

In conclusion, the results of the hot spot analysis, STC hot spot analysis, and the EHSA indicate there was significant clustering of use in the north-central region of the study area. The hot spot patterns within the hot spot analysis, STC hot spot analysis, and multiyear hot-spot analyses were similar in spatial distribution. However, the hot spot analysis was only capable of evaluating spatial clustering. The STC hot spot analysis and the EHSA analyses provided additional temporal information regarding use patterns that were not apparent in the raw telemetry data or hot spot analysis alone. This factor demonstrates the utility of evaluating wildlife telemetry data not only by spatial distribution but by temporal distribution as well.

Chapter 6 Discussion and Conclusions

Golden eagles at the Altamont have been studied for approximately 30 years which has led to a wealth of information regarding the population trends, collision risk potential, behavioral characteristics, and habitat preferences of this species (Smallwood et al. 2009, Hunt 2002, Hoover 2002, Smallwood 2007). Throughout the literature, ground squirrels have been cited as being a valuable resource for golden eagles and speculated to be a contributing factor relating to increased collision risk. Some studies have considered ground squirrel abundance as a metric for golden eagle resource selection, but the results were limited to smaller geographic areas within the Altamont and were limited to field-based approaches (Hoover 2002, Smallwood et al. 2009). As a result, the influence of ground squirrel distribution on non-adult golden eagle resource selection within the greater wind resource area was largely unknown.

To further understand this relationship, this study used a combination of approximately 20 years of ground squirrel burrow location data and high-resolution GPS telemetry to test this interaction across the entire Altamont. This study addressed the following questions: 1) What is the distribution of potential ground squirrel habitat at the Altamont based on historic burrow locations, 2) do non-adult golden eagles select locations while flying that have higher relative probabilities of ground squirrel occurrence, and 3) based on the telemetry data, are there consistent patterns of use within and across the spatial and temporal range of the study. This study was able to assess the influence of ground squirrel distribution on non-adult golden eagle resource selection and provide further information concerning patterns of use within the wind resource area. These results contribute to the understanding of golden eagles within the Altamont.

6.1. Overview of Analysis Results

This study was designed so that each analysis was derived from the previous step. As a result, these analyses should be evaluated in relationship to each other. Overall, this study found that the relative probability of ground squirrel occurrence at the Altamont is fairly consistent across the study area. Due to low predictive performance and violation of the heteroscedasticity assumption, it was inconclusive if potential ground squirrel distribution affected non-adult golden eagle resource selection within the study area. Even though the RSF model did not yield any relevant information regarding non-adult golden eagle habitat preferences, evaluation of the telemetry data using space-time pattern mining identified consistently used regions within the Altamont by non-adult golden eagles.

6.1.1. What is the distribution of potential ground squirrel habitat at the Altamont based on historic burrow locations?

The ground squirrel burrow points allowed for the successful creation of a relative probability of ground squirrel occurrence surface within the Altamont. The variables included within the final model and the ranges they represented were expected based on the available literature and life history of the species (Hubbart 2012, Lenihan 2007).

Having healthier vegetation during the early and late seasons (e.g. healthy vegetation is not common in August) increased the probability of ground squirrel occurrence and were the most important variables between replicates. Studies at the Altamont have qualitatively described the vegetation condition around burrow locations as being distinct from the greater landscape (Smallwood et al. 2009). Individuals are likely selecting for these patches of vegetation because they provide a food source during critical periods of the species life cycle (e.g. breeding) and offer concealment from predators (Smallwood et al. 2009, Hubbart 2012, Lenihan 2007). While grasses and forbs are the primary food source during the early months of the year (e.g. January to

June), this food source inevitably is not available during summer and fall requiring ground squirrels to shift their diet to other food sources. This study was unable to capture the potential shift in food source and future studies should attempt to quantify this as a variable to improve model performance. For example, it may not just be healthy vegetation, but the fact that the healthy vegetation is co-occurring in close proximity to favorable conditions for grasshoppers, which would provide a great source for nutrients and not require a shift of burrow location.

Slope position index had the largest contribution in the final ground squirrel distribution model with lower, but not flat, slope positions being preferred to ridge top positions. It is likely that ground squirrels are selecting for the lower slope positions for a few reasons. The first being they provide protection from aerial predators. The second reason is that lower slope positions potentially retain more water, facilitating healthy vegetation for longer. As expected, while the slope position category Valley resulted in the highest probability of ground squirrel occurrence, other slope positions also positively influenced the relative probability of ground squirrel occurrence which is consistent with findings of Smallwood et al. (2009). Flat slope positions negatively influenced the relative probability of ground squirrel occurrence. This reduced ground squirrel presence is likely due to tall vegetation that would reduce ground squirrels' ability to identify predators, increasing their vulnerability. Otherwise, it was inferred that other slope positions would not necessarily deter ground squirrel distribution because at high densities, individuals will occupy territories that may be suboptimal.

Soil type improved the relative probability of burrow occurrence, especially where fine and fine-loamy soil textures occur. These soil textures are conducive to supporting burrow systems as they are largely associated with friable qualities; free of large particulates, lower clay contents, and easily compactable (Jahn et al. 2006, Hubbart 2012).

The model AUC score of 0.782, indicates that the model was adequate for discerning the presence locations from background points, however having a higher AUC score would be preferred. Evaluation of the relative probability surface showed that most locations were capable of supporting ground squirrels. The general spatial pattern was that higher relative probabilities of ground squirrel occurrence increased in drainages where healthier vegetation and fine soils exist. Ridge tops were generally associated with lower relative probabilities of occurrence likely due to increased exposure to avian predators and fewer resources available. Based on the model results, it met the goal of this phase of the analysis which was to model ground squirrel distribution within the Altamont.

6.1.2. Do non-adult golden eagles select locations while flying that have higher relative probabilities of ground squirrel occurrence?

The influence of ground squirrel distributions on non-adult golden eagle resource selection within this study was uncertain due to the poor predictive performance of the model and violation of the heteroscedasticity assumption. Although the covariates in the final model for non-adult golden eagle RSF were consistent with other studies, both in the Altamont and western United States (Smallwood et al. 2009, Hunt 2002, Wiens et al. 2018, Watson, Duff, and Davies 2014, LeBeau et al. 2015), the level of effect of these covariates on resource selection in this study are inconclusive. There are several potential reasons why model performance was poor, which could include missing important predictor variables, the large differences in sample sizes, and a limited number of random effects.

The variables used in this analysis were selected because of their documented importance for golden eagle resource selection by other studies both at the Altamont and western United States. However, there were some variables unable to be accounted for that may be more important to non-adult golden eagles. One of the variables documented in other studies was distance to nest. While typically used in studies that have territorial individuals, the occupied territories surrounding the Altamont may play a larger role in the resource selection by non-adult golden eagles as conspecifics may be actively defending territories, driving younger birds away (Smallwood et al. 2009). Additionally, outside of nests, general information about other raptors that could be nesting within the study area that could affect non-adult golden eagle resource selection was not available.

In addition to interactions with conspecifics, wind has been documented as an important resource for golden eagle flight. This study was unable to capture a variable that would account for wind speed within the study area. The variables that were used in this analysis to encapsulate the effect of wind, orographic lift variables, were found to be colinear with eastness. Eastness was selected for inclusion over orographic lift because it incorporated all potential wind directions. However, while the eastness could be associated with dominant wind direction, the physical environmental component, wind speed, may vary over space in a way that was not captured in this analysis.

Leave-one-out cross-validation was used to evaluate the predictive performance of the model. During this process, the entire data from one individual was iteratively removed during the training and testing process until all individuals have been used for training and testing. While there are several benefits to this approach, such as using the entire dataset and reducing the effects of spatial autocorrelation, this may have negatively influenced the predictive performance of the model (Roberts et al. 2017). This is because there were large differences in the number of presence and available locations across all of the birds. Additionally, this study used a rather simple random effects structure only including a random effect for individual. There could be additional differences in habitat selection based on subadult age, sex, or even season (LeBeau et al. 2015). By incorporating these nested effects, the overall model may improve as more variation could be potentially explained using these factors.

The fact that the ground squirrel distribution variable did not make it into the final model may have been related to how the variable was used in this analysis, as no additional transformations were made to the logistic output. In other resource selection studies, distance has been used as a function to measure the effect of prey on resource selection, as golden eagles may forage in close proximity to prey without directly being directly over the burrow (LeBeau et al. 2015, Smallwood et al. 2009). In addition to distance from patch, another limitation of this variable was that it only served as a proxy for prey occurrence, but it did not actually capture prey abundance which may be more important to golden eagle resource selection (Hoover 2002). Finally, this variable was based on burrows collected over 20 years which did not explicitly capture how these locations may have shifted over time due to population dynamics and disturbance events (e.g. removal efforts) within the study area.

Conversely, the variable used as is may have been appropriate for assessing the effect on resource selection because golden eagle prey selection may vary by age class (Watson et al. 2018). Younger birds may not be as adept at hunting compared to adults and prey distribution may not matter. Additionally, because potential ground squirrel distribution was modeled using historic burrow locations, the range of variability within the model result may have been adequate to capture potential shifts in burrows as it would be expected that individuals would stay within suitable habitat. Finally, golden eagles are generalist predators and may be opportunistically foraging and selecting for locations with better uplift or higher winds and it may be more of an interaction between this variable and these features that is most important.

6.1.3. Are there consistent patterns of use by non-adult golden eagles within and across the spatial and temporal range of the study?

Hot spot analyses are commonly used to explore spatial patterns of events. The use of hot spot analysis within this study provided useful information about the larger trends in site use by non-adult golden eagles. However, this analysis does not consider temporal effects on hot spots. This highlights the importance of considering both space and time when evaluating event data.

The space-time cube hot spot analysis allowed for the 3D visualization of patterns of use by non-adult golden eagles within the study area. The ability to visualize these hot spot patterns in 3D format is more informative than the hot spot analysis or visual inspection of the raw telemetry data alone. One of the more interesting results from this process included distinct temporal clusters in the data and the spatial overlap of these trends. Additionally, from approximately the end of March 2017 through December 2018, no trends were detected. These differences in use patterns may be tied to other significant events in the non-adult golden eagle life cycle such as migration or dispersal. Furthermore, when doing subsequent analysis (e.g. EHSA), the STC Explorer was a useful tool to better understand the conditions that led to each EHSA classification (e.g. Consecutive Hot Spot).

This analysis used several spatial and temporal neighborhoods to evaluate patterns in the use of the study area. There were little differences between the two spatial neighborhoods evaluated which may indicate that these were sufficient in meeting the optimal range for this analysis. While the patterns based on spatial neighborhood size were relatively similar, the temporal windows did not share this same result. In general, as larger temporal neighborhoods were considered, the stronger the patterns became. The Esri help pages about the EHSA suggest that there is an "optimal" neighborhood size for neighborhood settings that may be found through trial and error (Esri 2018). The findings from this study support this concept. When using a too large or too small a temporal neighborhood, patterns may be overstated or go unrecognized. Similar to the way the seasonal analysis results were not informative in this study, trends in the multiyear analysis may have been overstated.

While believed to be sufficient for this study, the optimal neighborhoods used for the EHSA may not have been either the 3,000 or 5,000m spatial neighborhood, nor the season, year, or multiyear temporal neighborhood. Considering the differences in patterns from each of these analyses, the optimal space-time neighborhoods could have easily been a 4,000m spatial neighborhood and a two-year temporal neighborhood. However, the general patterns that existed in the data were very informative regarding non-adult golden eagle use of the study area. The north-central region of the study area shows significant use by the eagles within this study and this area should be evaluated for what qualities make it attractive for golden eagle use.

The hot spot analysis, STC, and EHSA tools on their own can provide very useful information regarding space-time patterning. However, this analysis demonstrates that the utility of these tools is far greater when they are used in tandem. Space-time pattern mining tools were incredibly useful in this study and are underutilized within the field of wildlife ecology. This analysis demonstrates why evaluating the data using these techniques, or similar methods, is important to include in analysis of habitat preference.

6.2. Future Work

While this analysis was mostly able to address the questions posed in Chapter 1, there are several improvements that could be made in future studies that may yield different results. To assess the effect of ground squirrel distribution at the Altamont on eagle distributions, this study modeled the relative probability of ground squirrel occurrence. However, this metric is not associated with abundance estimates. Having actual abundance estimates of ground squirrel may be a more informative metric to evaluate the effect of prey on resource selection by golden eagles. Additionally, accounting for the varying levels of rodent control that have occurred and may still be occurring at the Altamont would be beneficial to include into future models. This factor may be significant because rodent control is thought to be the largest driver of ground squirrel abundance (Hunt and Hunt 2006). Future studies should attempt to account for these factors as they may better reflect the true distribution of ground squirrels at the Altamont and improve the accuracy of a model evaluating ground squirrel distribution or abundance.

This analysis was limited to only analyzing non-adult golden eagles for the RSF modeling. Future resource selection models should aim to include both adults and non-adults because of the potential effect of age on foraging capabilities and live prey reliance (Watson et al. 2018). Additionally, the potential effect of wind turbine density and distribution on resource selection or avoidance was unaccounted for within this study. This factor could influence how individuals utilize the study area resulting in the selection for less optimal foraging locations. Future analyses should attempt to incorporate these factors to evaluate how they may influence resource selection by golden eagles.

Furthermore, this study was unable to assess the relative importance of the Altamont to individual eagles evaluated in this study as data were only available within the study area and not for the entire home range of individuals. Having the complete data set would have been preferred so that estimation of effects would have been in proportion to the relative use in the individuals home range. Furthermore, this analysis used a relatively simplistic random effects structure as it only included a random intercept for individuals. Future studies should consider incorporating a more complex random effects structure which should allow for differences in seasonal use, sex, or interannual variation in resource selection (LeBeau et al. 2015). In addition to the random effects structure, future studies should incorporate variables that provide a better measure for wind speed and compensate for the effect of inter- and intra-species dynamics.

To determine the effect of ground squirrel distribution on non-adult golden eagle resource selection, this study uses the logistic output without additional modification. This variable may have been more informative with some manipulation. Future studies could identify a meaningful patch size (e.g. two contiguous acres of high probability) and then use a distance function to evaluate golden eagle resource selection. This would be supported by the literature which suggests that golden eagles may avoid areas which have higher densities of ground squirrels, but remain in some proximity to these features so that they are concealed when they do decide to capture prey (Smallwood et al. 2009). Additionally, the variable could be converted to a binary format so that a cut off value, such as a relative probability of 0.7, could be used to designate locations as only high and low probabilities. This might provide a larger contrast than the fine-scale probability differences at 30m resolution. Future analyses should consider different derivatives of this logistic output that may be better metrics to capture how golden eagles use their environment.

Future studies should continue to explore the utility of hot spot analyses, STCs, and EHSAs in evaluating the patterns that may exist in telemetry data. While not possible in this study, a robust RSF model can be used to generate a relative prediction surface to visualize the relative probability of selection spatially. The EHSA could potentially be used to validate these predictions where hot spots in telemetry data could be associated with higher probabilities of selection. Additionally, future studies could evaluate variations in quantity, arrangement, and distribution of important resources identified in an RSF and compare these resources between hot and cold spots to better understand how differences in these factors may influence selection.

Another route that could also be taken when developing the STCs and EHSAs is to further subset the data to explore how hot and cold spots shift by behavior (e.g. consider flight versus perch points).

6.3. Conclusion

This study demonstrated a method to evaluate the relationship between prey distribution and eagle resource selection. However, this study evaluated only one of the many possible ways this relationship can be investigated. While addressing most of the questions posed in Chapter 1, there were some shortcomings that have been outlined above. Due to the inconclusive results of the RSF, the effect of prey distribution on non-adult golden eagle resource selection is still largely unknown. Future studies should continue to evaluate the potential influence of prey on resource selection by golden eagles. While the RSF did not produce ideal results, the hot spot analysis, STC hot spot analysis, and EHSA analyses were able to highlight important spatiotemporal patterns of use. Future studies should strongly consider incorporating this type of analysis to fully exploit the data collected from telemetry studies.

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Appendix A – Enlarged Figures from Text

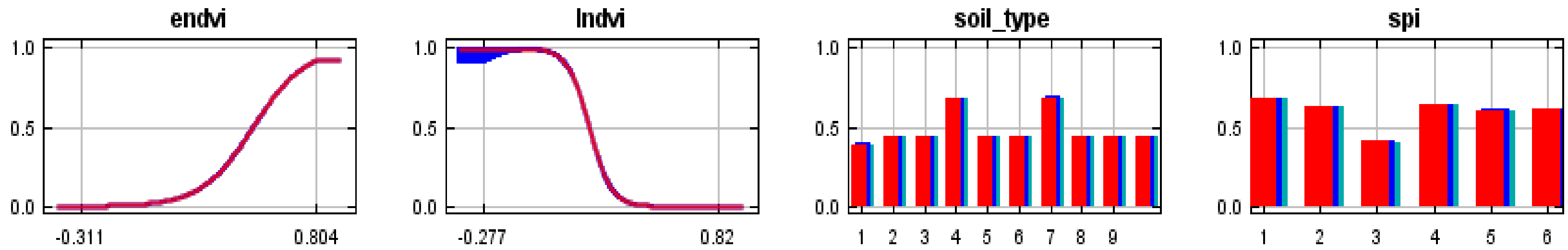

Figure 59 - Enlarged marginal response curves for each variable within the final Maxent model. Each graph shows how the variable of interest influenced the model's predictive ability. The x-axis represents the variable range and the y-axis represents the relative probability of occurrence.

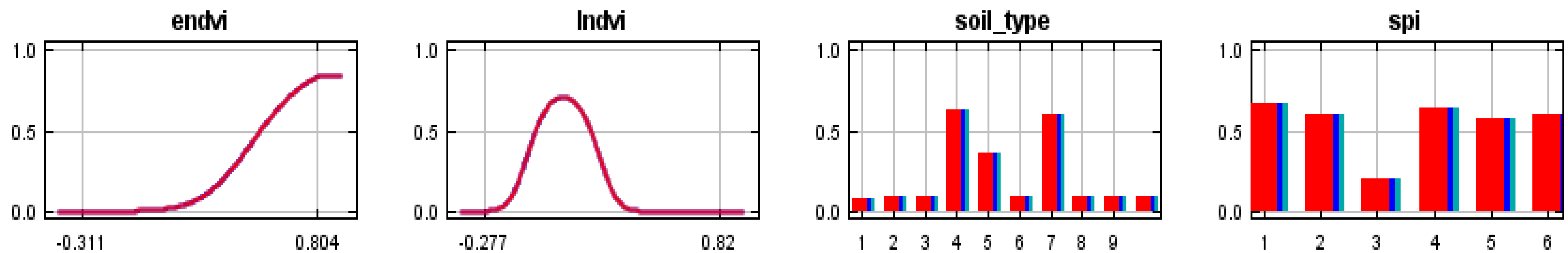

Figure 60 - Enlarged response curves from separate univariate models. These models were from the same model run as above but they are intended to show how variable response may have differed across model replicates. The x-axis represents the variable range and the y-axis represents the relative probability of occurrence.

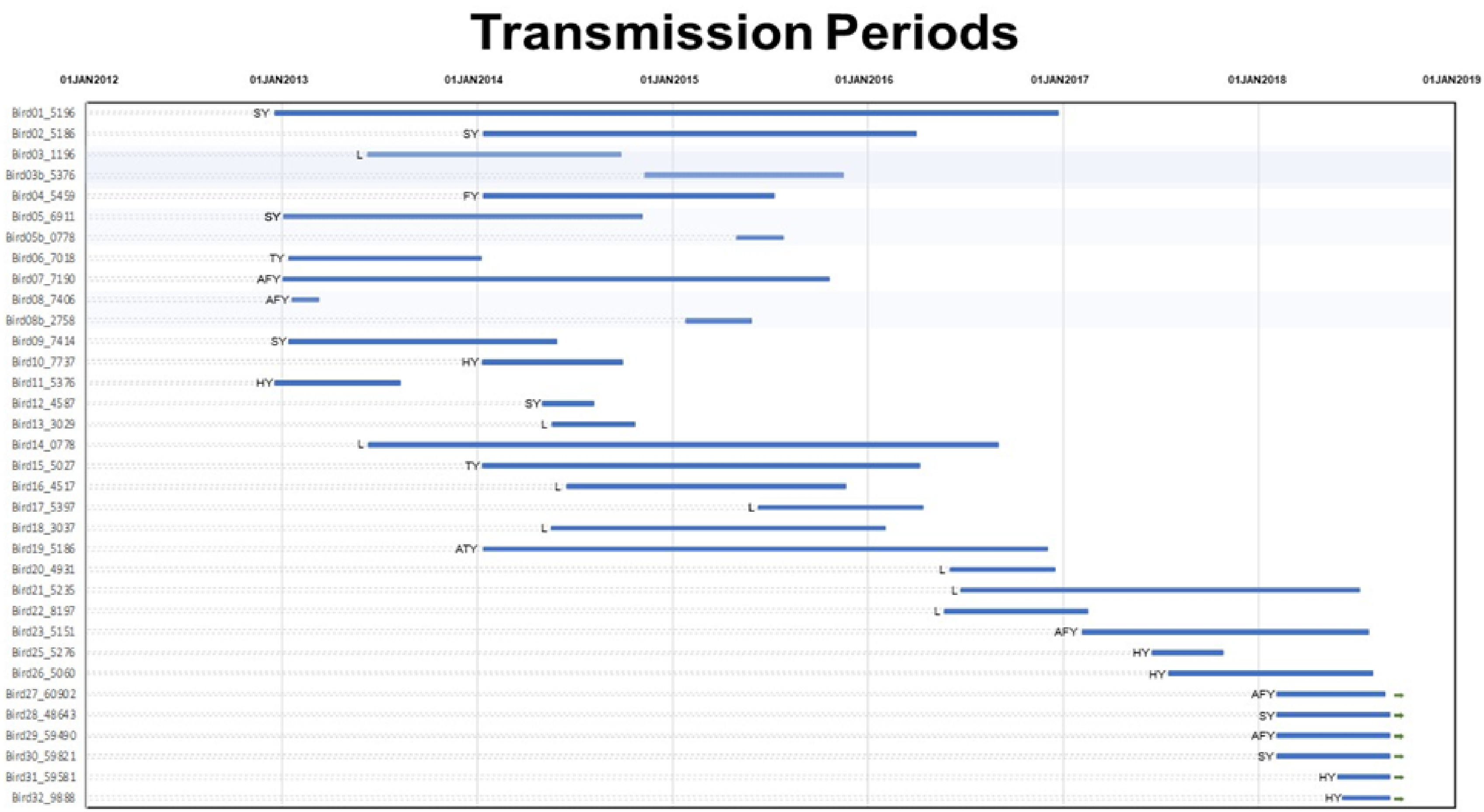

Figure 61 – Enlarged transmission period chart for all telemetered golden eagles. This chart shows the transmission periods for all individuals not just the individuals used within this study. Age classes include L = nestling, HY = hatch year, SY = second year, TY = third year, ATY = after third year, FY = fourth year, AFY = after fourth year or adult. Source: Lee Neher

Appendix B – Emerging Hot Spot Analysis and Space-Time Cube Supplemental Information

Table 11 - Classification of hot and cold spots used within the EHSA tool. Source: http://desktop.arcgis.com/en/arcmap/10.3/tools/space-time-pattern-mining-toolbox/learnmoreemerging.htm#GUID-09587AFC-F5EC-4AEB-BE8F-0E0A26AB9230.

Pattern Type	Description
No Pattern	Does not meet the conditions of hot or cold spots.
New Hot/Cold Spot	A location that is a statistically significant hot/cold spot for the final time step and has never been a statistically significant hot/cold spot before.
Consecutive Hot/Cold Spot	A location with a single uninterrupted run of statistically significant hot/cold spot bins in the final time-step intervals. The location has never been a statistically significant hot/cold spot prior to the final hot/cold spot run and less than 90 percent of all bins are statistically significant hot/cold spots.
Intensifying Hot/Cold Spot	A location that has been a statistically significant hot/cold spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant.
Persistent Hot/Cold Spot	A location that has been a statistically significant hot/cold spot for 90 percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.
Diminishing Hot/Cold Spot	A location that has been a statistically significant hot/cold spot for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant.
Sporadic Hot/Cold Spot	A location that is an on-again then off-again hot/cold spot. Less than 90 percent of the time-step intervals have been statistically significant hot/cold spots and none of the time-step intervals have been statistically significant cold/hot spots.
Oscillating Hot/Cold Spot	A statistically significant hot/cold spot for the final time-step interval that has a history of also being a statistically significant cold/hot spot during a prior time step. Less than 90 percent of the time-step intervals have been statistically significant hot/cold spots.
Historical Hot/Cold Spot	The most recent time period is not hot/cold, but at least 90 percent of the time-step intervals have been statistically significant hot/cold spots.

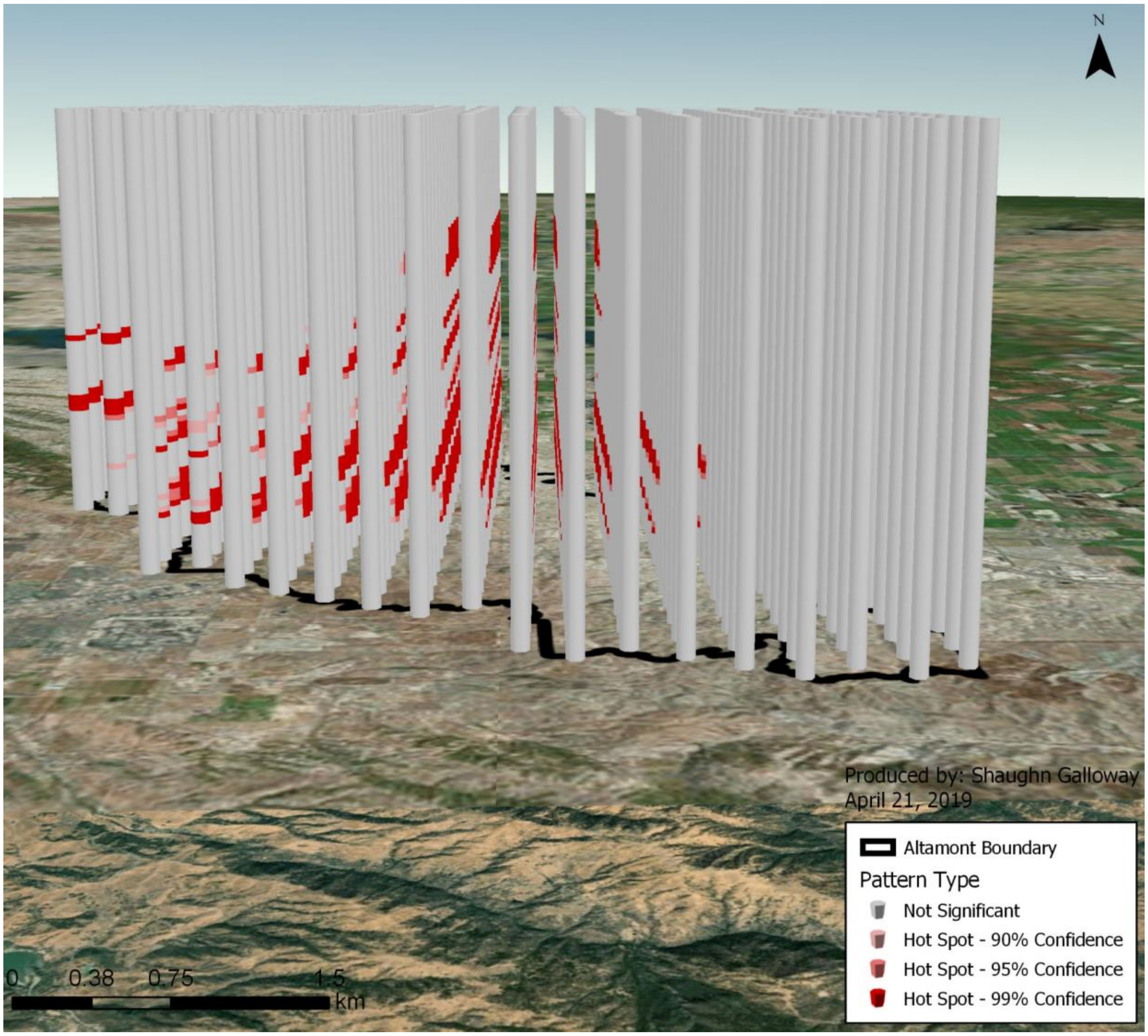

Figure 62 – STC hot spot analysis viewed from the south. Altamont boundary provided by Doug Bell and Lee Neher.

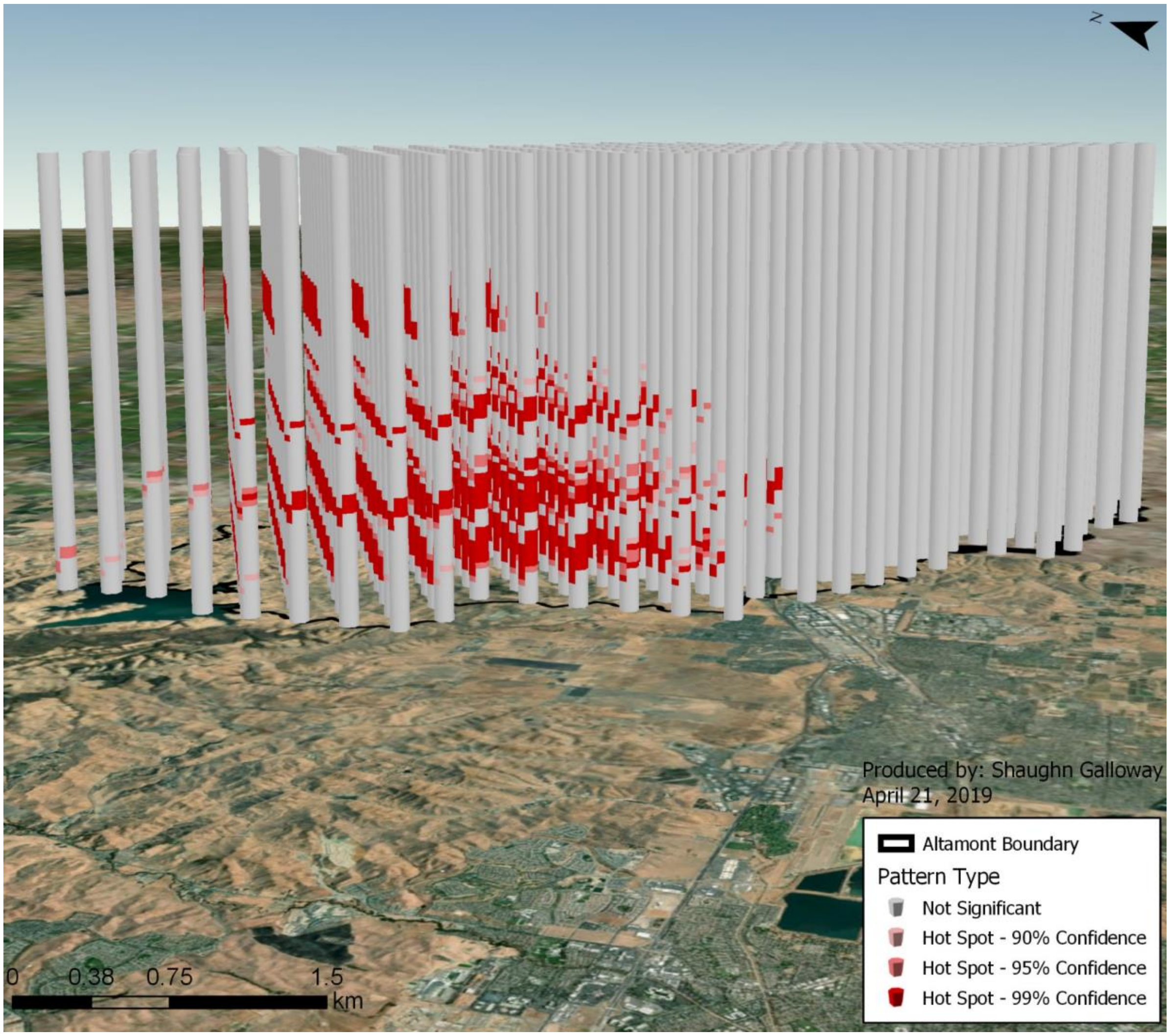

Figure 63 - STC hot spot analysis viewed from the west. Altamont boundary provided by Doug Bell and Lee Neher.

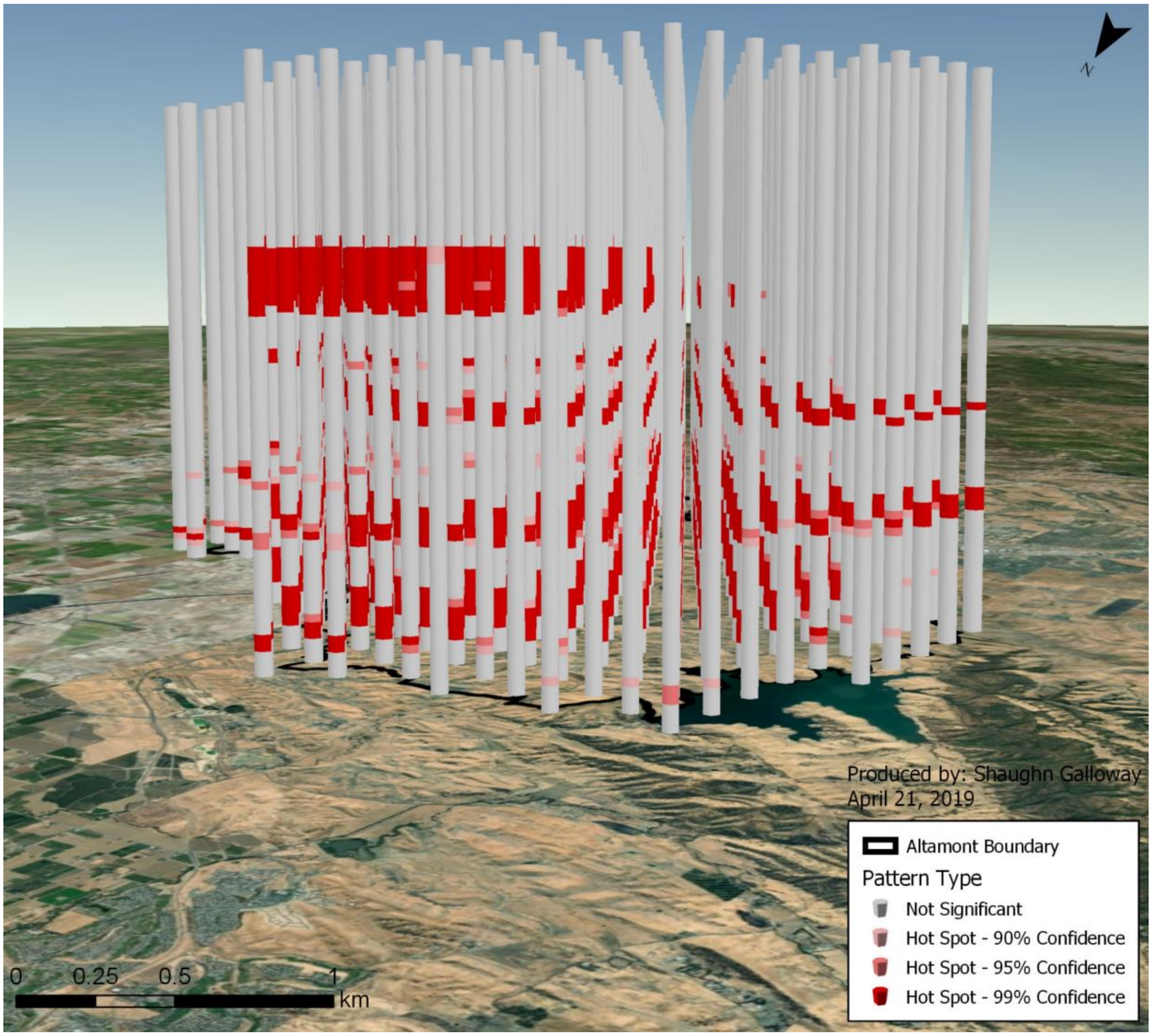

Figure 64 – STC hot spot analysis viewed from the north. Altamont boundary provided by Doug Bell and Lee Neher.

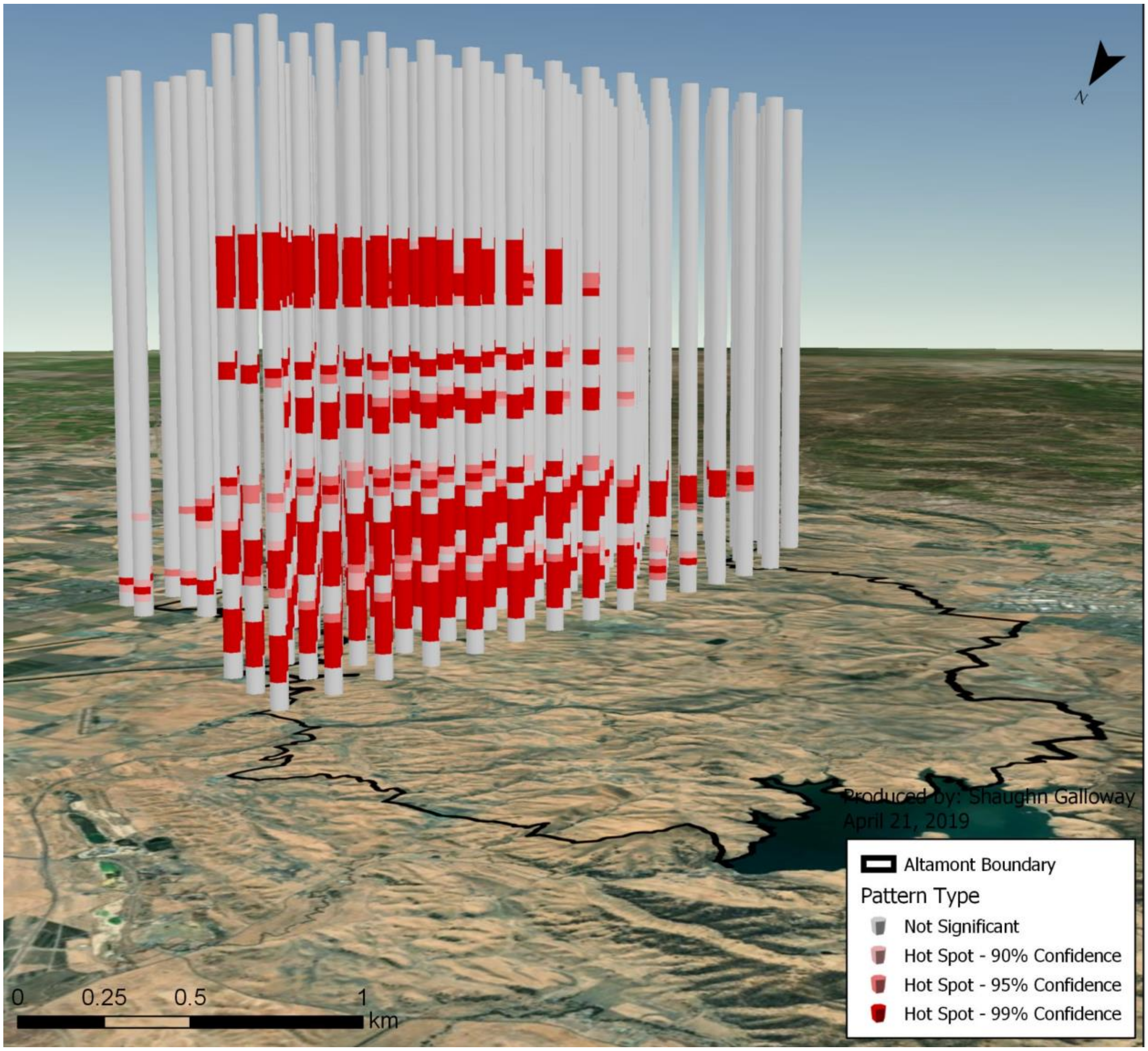

Figure 65 – STC hot spot analysis only displaying southern columns to provide an inside look into the STC. Viewed from the north. Altamont boundary provided by Doug Bell and Lee Neher.

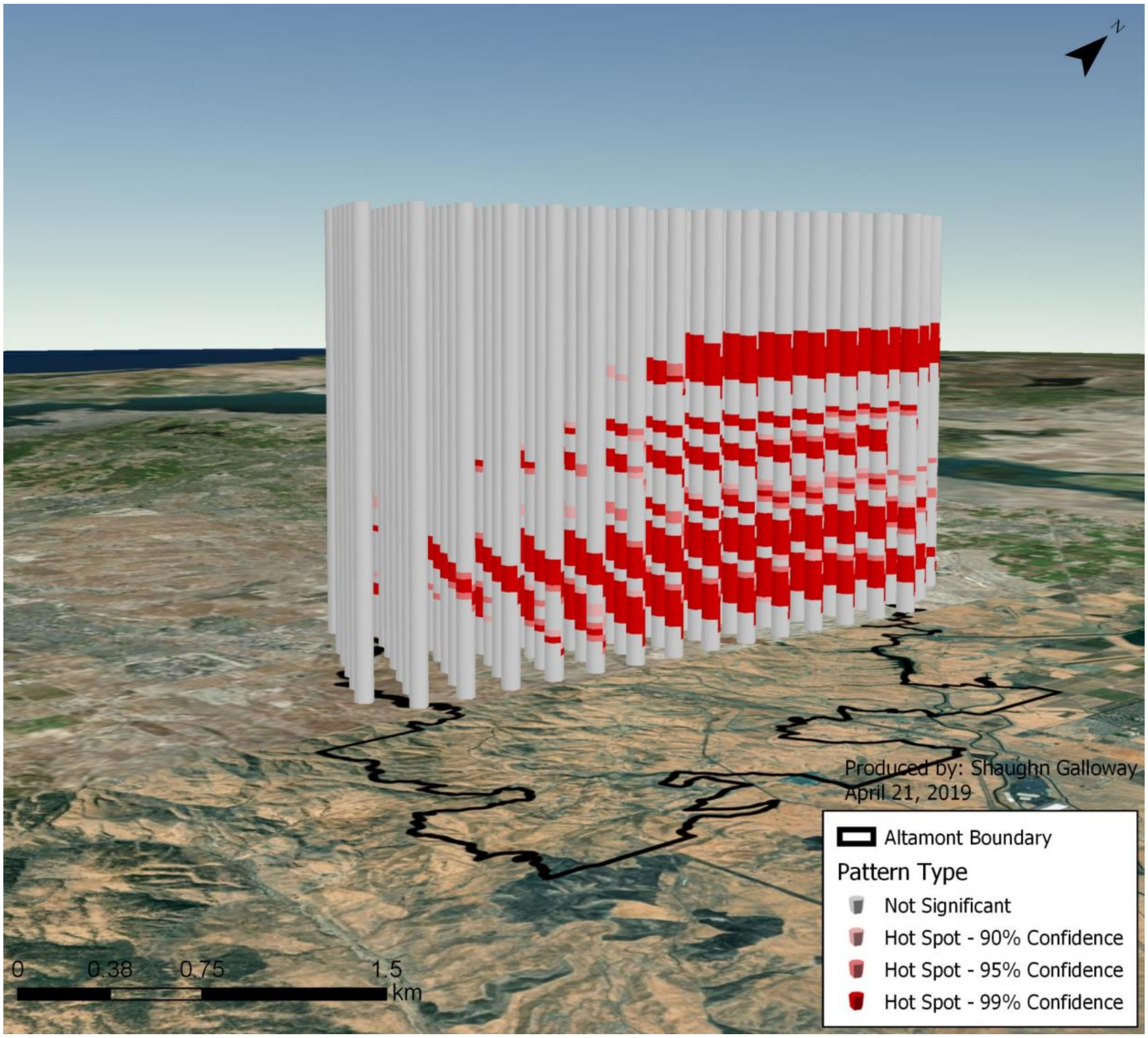

Figure 66 – STC hot spot analysis only displaying northern columns to provide an inside look into the STC. Viewed from the southeast. Altamont boundary provided by Doug Bell and Lee Neher.

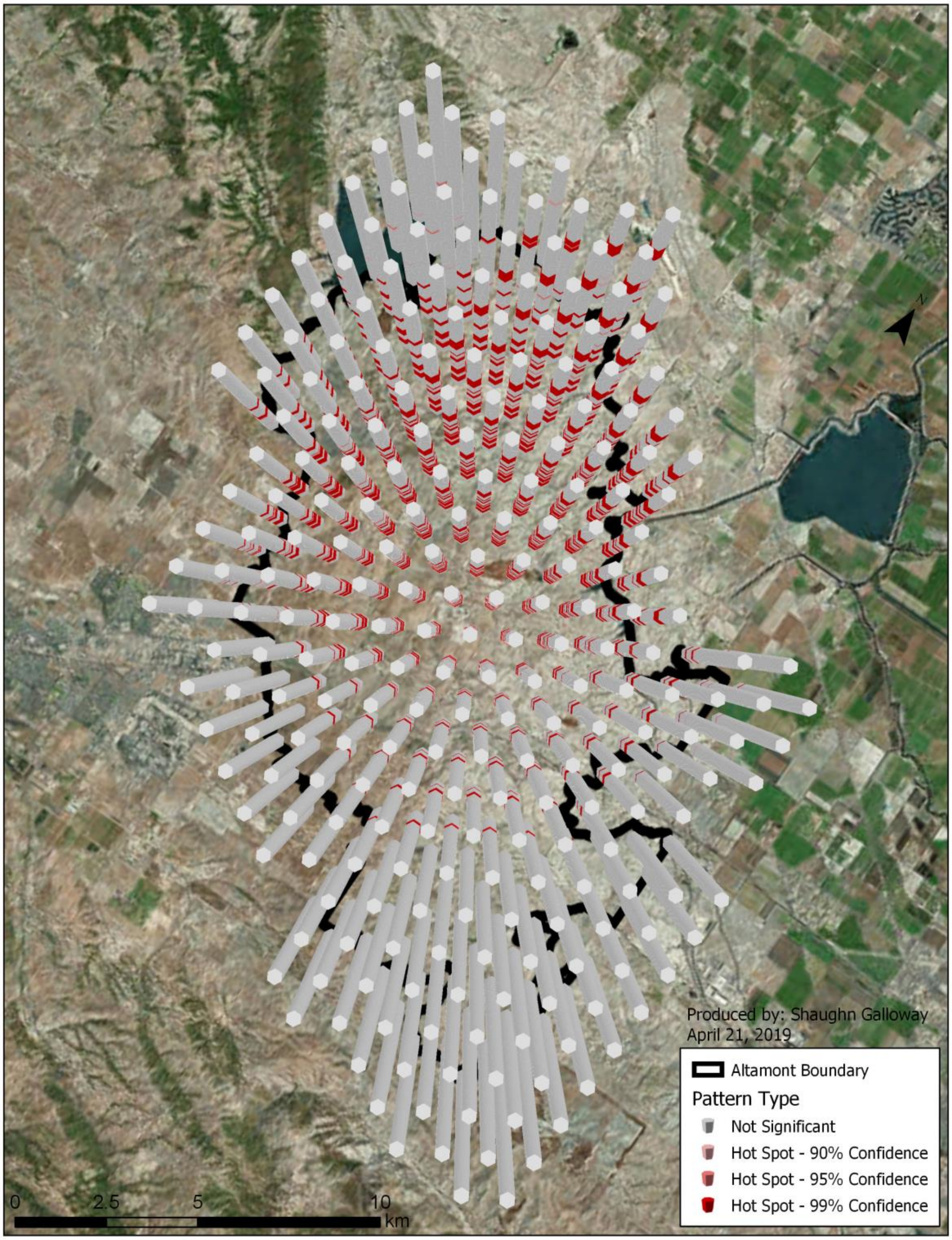

Figure 67 – STC hot spot analysis viewed from above. Altamont boundary provided by Doug Bell and Lee Neher.

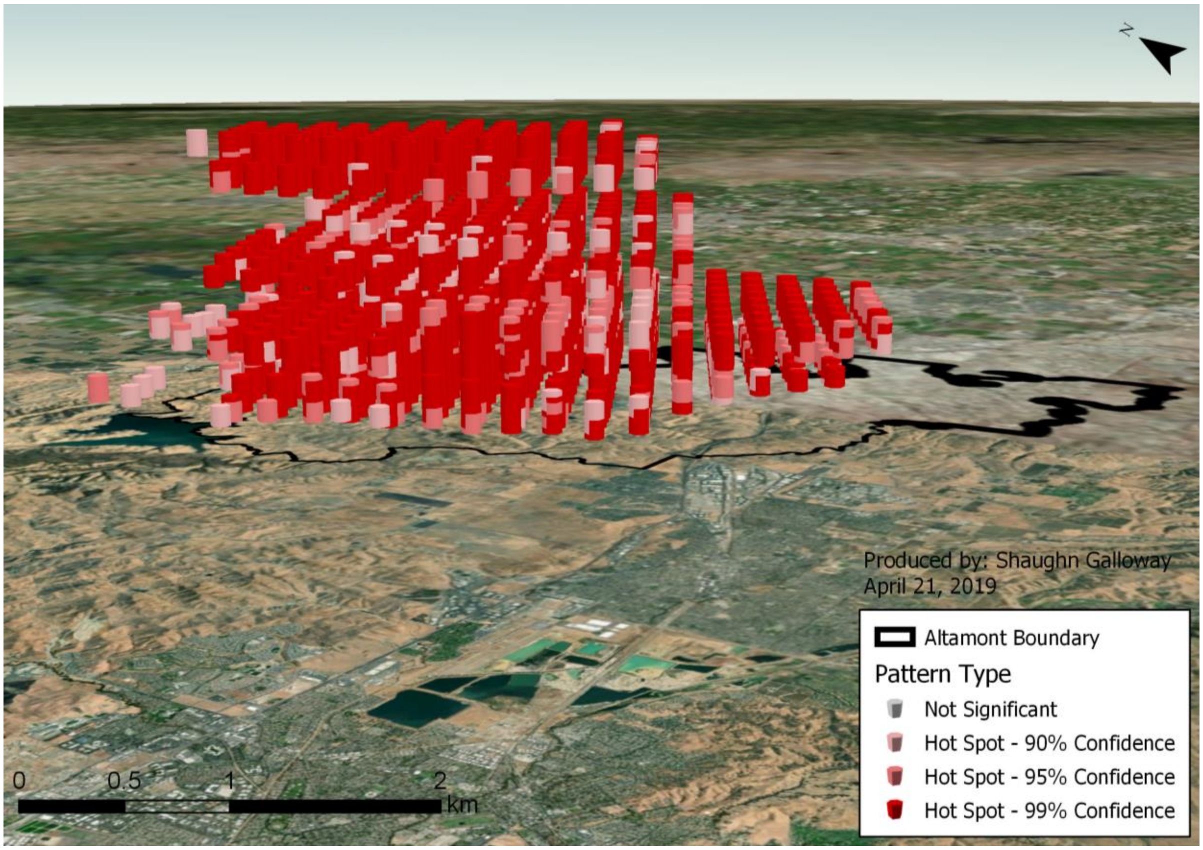

Figure 68 – Spatial extent of statistically significant hot spots. Viewed from the west. Altamont boundary provided by Doug Bell and Lee Neher.